

VIRTUAL POWER PLANT OPERATION OPTIMIZATION

BY

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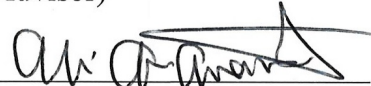


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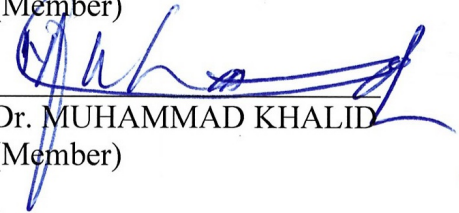
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DEDICATION

I would like to dedicate my dissertation work to everyone who stood by my side and encouraged me. A special thanks to my family and my close friends. I dedicate this work first of all to my mother who eagerly wanted to see me at this stage, and my beloved dad who inspired me to move forward.

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LIST OF ABBREVIATIONS

ABC Artificial Bee Colony

AC Ant Colony

ACF Autocorrelation function

ADN Active Distribution Network

AI Artificial Intelligence

AIC Akaike's Information Criteria

ANN Artificial Neural Network

AR Autoregressive

ARIMA Autoregressive integrated moving average

ARMA Autoregressive moving average

BIC Bayesian Information Criteria

CHP Combined Heat and Power

CVPP Commercial Virtual Power Plant

CVaR Conditional value at risk

DA Day ahead

DER Distributed Energy Resources

DG Distributed Generation

DR Demand Response

DSM Demand Side Management

DSO Distribution system operator

EACF Extended autocorrelation function

EMS Energy Management System

EP Energy pool

ESS Energy Storage Systems

EU European Union

EV Electric Vehicles

FF Firefly

GA Genetic Algorithm

GAMS General Algebraic Modeling System

HP Hydropower

ICT Information and Communication Technologies

IoT Internet of Things

LA Load Aggregator

LDC Load Duration Curve

LP Linear Programming

MA Moving average

MC Microgrid

MCS Monte Carlo Simulation

MILP Mixed Integer Linear Programming

MINLP Mixed Integer Non-Linear Programming

NLP Non-Linear Programming

P2P Peer to peer

PACF Partial autocorrelation function

PEU Power exchange unit

PHEV Plug-in Hybrid Electric Vehicle

PSO Particle Swarm Optimization

PV Photovoltaic

QPSO Quantum Particle Swarm Optimization

RDG Renewable distributed generation

RES Renewable Energy Sources

RMSE Root mean square error

RT Real time

SARIMA Seasonal autoregressive integrated moving average

SARIMAX Seasonal autoregressive integrated moving average with exogenous variable

SOC State of charge

SOS Special order set

TSO Transmission System Operator

TVPP Technical Virtual Power Plant

VPP Virtual Power Plants

WDU Water desalination unit

WT Wind Turbines

- **Indexes**

c = Conventional power plants

d = Demands

ℓ = Network lines.

n = Network nodes

r = Stochastic renewable generating units

$r(\ell)$ = Receiving – end node of network line ℓ

s = Storage units

$s(\ell)$ = Sending – end node of network line ℓ

t = Time periods

ω = Scenarios

v = Iterations of the column – and – constraint generation algorithm

- **Sets**

Π^{DA} = Realizations of uncertain parameters of the DA market

Π^{RT} = Realizations of uncertain parameters of the RT market

Ω^{C} = Conventional power plants

Ω^{D} = Demands

Ω_n^{D} = Demands located at node n

Ω^{G} = Generating units

Ω_n^{G} = Generating units located at node n

Ω^{L} = Network lines

Ω^{N} = Network nodes

Ω^{R} = Stochastic renewable generating units

Ω^{S} = Storage units

Ω_n^{S} = Storage units located at node n

Ω^{W} = Water desalination units

Ω^{T} = Time periods

Ψ_{dt}^{D} = Feasibility set of demand d in time period t

Ψ_{gt}^{G} = Feasibility set of generating unit g in time period t

- **Parameters**

B_ℓ = Line ℓ susceptance [S]

$\underline{C}_c^{\text{C}}$ = Conventional power plant shut down cost c [$\$$]

$\overline{C}_c^{\text{C}}$ = Conventional power plant shut down cost c [$\$$]

$C_c^{\text{C},F}$ = Conventional power plant online cost c $\left[\frac{\$}{\text{h}} \right]$

$C_c^{\text{C},V}$ = Conventional power plant variable production cost c $\left[\frac{\$}{\text{MWh}} \right]$

$\underline{E}_d^{\text{D}}$ = Minimum energy consumption of d throughout the planning horizon [MWh]

$\underline{E}_{st}^{\text{S}}$ = Lower bound of the energy stored in storage unit s in time period t [MWh]

$\overline{E}_{st}^{\text{S}}$ = Upper bound of the energy stored in storage unit s in time period t [MWh]

$\underline{P}_c^{\text{C}}$ = Minimum power production of conventional power plant c [MW]

$\overline{P}_c^{\text{C}}$ = Maximum power production of conventional power plant c [MW]

$\underline{P}_{dt}^{\text{D}}$ = Lower bound of the power consumption of demand d in time period t [MW]

$\overline{P}_{dt}^{\text{D}}$ = Upper bound of the power consumption of demand d in time period t [MW]

$\overline{P}_\ell^{\text{L}}$ = Capacity of network line ℓ [MW]

$\overline{P}_{rt}^{\text{R}}$ = Available production of unit r in time period t [MW]

$\overline{P}_s^{\text{S},C}$ = Charging capacity of storage unit s [MW]

$\overline{P}_s^{\text{S},D}$ = Discharging capacity of storage unit s [MW]

$$\begin{aligned}
R_c^{C,D} &= \text{Down ramping limit of conventional power plant } c \left[\frac{\text{MW}}{\text{h}} \right] \\
R_c^{C,SD} &= \text{Shut down ramping limit of conventional power plant } c \left[\frac{\text{MW}}{\text{h}} \right] \\
R_c^{C,SU} &= \text{Start up ramping limit of conventional power plant } c \left[\frac{\text{MW}}{\text{h}} \right] \\
R_c^{C,U} &= \text{Up ramping limit of conventional power plant } c \left[\frac{\text{MW}}{\text{h}} \right] \\
R_d^{D,D} &= \text{Down ramping limit of demand } d \left[\frac{\text{MW}}{\text{h}} \right] \\
R_d^{D,U} &= \text{Up ramping limit of demand } d \left[\frac{\text{MW}}{\text{h}} \right] \\
X_\ell &= \text{Reactance of network line } \ell \text{ } [\Omega] \\
\Delta t &= \text{Duration of time periods [h]} \\
\eta_s^{S,C} &= \text{Charging efficiency of storage unit } s \text{ } [\%] \\
\eta_s^{S,D} &= \text{Discharging efficiency of storage unit } s \text{ } [\%] \\
\bar{P}_n^M &= \text{Maximum power that can be traded with the grid at node } n \text{ [MW].} \\
P_{rt}^{R,A} &= \text{Maximum production of renewable unit } r \text{ in time period } t \text{ [MW].} \\
\bar{P}^V &= \text{Power capacity of generation assets (positive) in the VPP [MW].} \\
\underline{P}^V &= \text{Power capacity of consumption assets (negative) in the VPP [MW].} \\
U_{dt}^D &= \text{Utility of demand } d \text{ in time period } t \left[\frac{\$}{\text{MWh}} \right]. \\
\lambda_t^{\text{DA}} &= \text{DA energy market price in time period } t \left[\frac{\$}{\text{MWh}} \right]. \\
\lambda_t^{\text{RT}} &= \text{RT energy market price in time period } t \left[\frac{\$}{\text{MWh}} \right]. \\
\tilde{P}_{rt}^{R,A} &= \text{Average production of renewable unit } r \text{ in time period } t \text{ [MW].} \\
\hat{P}_{rt}^{R,A} &= \text{Production fluctuation of renewable unit } r \text{ in time period } t \text{ [MW].} \\
\alpha &= \text{Confidence level for CVaR calculation} \\
\beta &= \text{Weighing parameter between profit and CVaR} \\
\Gamma_r^R &= \text{Uncertainty budget of unit renewable unit } r \\
Wd_{wty}^{WDU} &= \text{Water demand from the WDU } [m^3] \\
Wd_w^{peak} &= \text{daily peak water demand from the WDU } [m^3] \\
Wd_{wt}^{profile} &= \text{normalized water demand from the WDU} \\
PE_w^{WDU} &= \text{Electric power consumption of the WDU } [kW/m^3] \\
K_{joule}^{kwh} &= \text{Conversion from Mega Joule to kW [0.277778]} \\
PT_w^{WDU} &= \text{Thermal energy consumption of the WDU } [MJ/m^3] \\
Wg_w^{HC} &= \text{Hourly maximum water generation capacity of the WDU } [m^3/h] \\
Wg_w^{TDC} &= \text{Total daily water generation capacity of the WDU } [m^3] \\
WPC_w^{Cha} &= \text{Water charging capacity of the tank of the WDU } [m^3] \\
WPC_w^{Dis} &= \text{Water discharging capacity of the tank of the WDU } [m^3] \\
M &= \text{a big value positive constant} \\
WC_w^{Tank} &= \text{Total capacity of the tank of the WDU } [m^3]
\end{aligned}$$

X_t^{lim} = a value to decide the reliability of participation into the markets

U_{wt}^{WDU} = Utility of demand of the WDU in time period t $\left[\frac{\$}{\text{MWh}}\right]$.

- **Variables**

e_{st}^S = Energy stored in storage unit s in time period t [MWh]

p_{ct}^C = Power generation of conventional power plant c in time period t [MW]

p_{dt}^D = Power consumption of demand d in time period t [MW]

p_{gt}^G = Power generation of generating unit g in time period t [MW]

$p_{\ell t}^L$ = Power flow through line ℓ in time period t [MW]

p_{rt}^R = Production of stochastic renewable generating unit r in time period t [MW]

$p_{st}^{S,C}$ = Charging power level of storage unit s in time period t [MW]

$p_{st}^{S,D}$ = Discharging power level of storage unit s in time period t [MW]

u_{ct}^C = Binary variable equal to 1 if c is generating electricity in period t , 0 otherwise

u_{st}^S = Binary variable to prevent simultaneous charge & discharge of s in period t

$v_{ct}^{C,SD}$ = Binary variable equal to 1 if c is shut down in period t , 0 otherwise

$v_{ct}^{C,SU}$ = Binary variable equal to 1 if c is started up in period t , 0 otherwise

δ_{nt} = Voltage angle at bus n in time period t [rad]

$\bar{c}_{ct}^C$ = Auxiliary variable to linearize start up cost of unit c in time t [\$].

$\underline{c}_{ct}^C$ = Auxiliary variable to linearize shut down cost of unit c in time t [\$].

p_t^{DA} = Power scheduled to be bought from, sold to (if negative, positive) the DA energy market in time period t [MW].

p_{nt}^M = Power scheduled to be bought from/sold to (if negative/positive) the Day-ahead and real-time energy markets at node n in time period t [MW].

p_t^{RT}
= Power scheduled to be bought from, sold to (if negative, positive) the RT energy market in time period t [MW].

p_{st}^S = Net power level of storage unit s in time period t [MW].

μ = Auxiliary variable to linearize CVaR [\$]

ρ = Value at risk measure [\$]

ζ = Total profit of the VPP over the planning frame[\$]

$C_{ct\gamma}^{C,V,F}$ = Conventional generator variable and fixed costs[\$]

$p_{ct\gamma i}^C$ = Auxiliary positive variables for generator variable cost

$y_{ct\gamma i}$ = Auxiliary binary variables for generator variable cost

$Wg_{wt\gamma}^{Tank}$ = Water generated by the tank of the WDU [m^3]

$Wg_{wt\gamma}^{WDU}$ = Water generated by the WDU [m^3]

$Pa_{wt\gamma}^{WDU}$ = Total equivalent electric demand of the WDU [MW]

$W_{wt\gamma}^{Dis}$ = Discharged water from the tank of the WDU [m^3]

$W_{wt\gamma}^{Cha}$ = Charged water to the tank of the WDU [m^3]

$BT_{wt\gamma}^{Cha}$ = Charging indicator of the tank of the WDU

$BT_{wt\gamma}^{Dis}$ = Discharging indicator of the tank of the WDU

$W_{wt\gamma}^{Tank}$ = Water stored in the tank of the WDU [m^3]

$p_{t\omega\gamma}^{sum}$ = Power balance at each hour [MW]
 $B_{t\omega\gamma}^{sum1}$ = Binary variable to detect the sign of the power balance
 $B_{t\omega\gamma}^{sum2}$ = Binary variable to detect the sign of the power balance
 EP^{profit} = Profit/loss made by the energy pool
 VPP_{EP}^{profit} = Profit/loss made by the VPP
 $\lambda_y^{RT,act}$ = The real time market price at hour y
 $p^{to,EP}$ = Power supplied from the VPP to the EP
 $C_{ct\gamma}^C$ = *Conventional generator operational cost*[\$]
 $p_{wt\omega\gamma}^{WDU}$ = Power consumption of the WDU unit w in time period t [MW]
 $p_{ct}^{C,max}$ = Intermediate variable for maximum power generation of conventional power plant c in time period t [MW]

ABSTRACT

Full Name : [HUSSEIN ADEL ABDELAZIM ABDELLATIF]
Thesis Title : Virtual Power Plant Operation Optimization
Major Field : [Electrical Engineering]
Date of Degree : [May 2022]

A virtual power plant is considered as a microgrid that trades power with the electricity markets and that does not work in an islanded scheme. Virtual power plants have attracted attention over the past years and even decades and some virtual power plants have been practically implemented such as Next Kraftwerke, Germany. Virtual power plants may have a centralized, distributed or comprehensive control scheme. Based on the control scheme, the optimization/ operation of the virtual power plant is designed. In this research, a comprehensive literature survey on the major mixed integer linear programming models on the operation optimization of the virtual power plants will be done. After that, a comprehensive virtual power plant optimization model will be constructed comprising dispatchable and non-dispatchable generators with their comprehensive constraints based on the models studied in literature. Then, the first objective optimization problem will be designed to achieve operational cost minimization and profit maximization as well. Additionally, risk factor will be considered through the use of conditional value at risk representation. Next, reliability constraints for the system power balance security will be developed and tested for effectiveness. Using those reliability constraints along with the previous objectives, a multi-objective optimization problem will be formulated. It is proposed to include a water desalination unit (WDU) as a specific load type due to its importance especially in countries that rely heavily onto water desalination such as Saudi Arabia. Water desalination units have a huge infrastructure and they can serve as virtual

storage units. These reasons make it very essential to consider such type of load and to consider its way of interaction with the electrical network. The virtual power plant will participate in both the day-ahead and real-time markets. An improved auto regressive moving average model is proposed and a special-order set type two model is also tested for the representation of piecewise linear functions representation in linear programming since the conventional generator variable cost is approximated as a piecewise linear function. Lastly, a virtual power plant cluster is proposed, designed, simulated, and tested as a newly introduced concept in this research that is analogous to the microgrid cluster concept. The final design proposed in this research will have extremely high reliability such that it shall not fail to balance the power at any hour of the day.

ملخص الرسالة

الاسم الكامل: حسين عادل عبد العظيم عبد اللطيف

عنوان الرسالة: تحسين تشغيل محطات الطاقة الافتراضية

التخصص: هندسة كهربائية

تاريخ الدرجة العلمية: مايو 2022

تعتبر محطة الطاقة الافتراضية بمثابة شبكة صغيرة تتداول الطاقة مع أسواق الكهرباء ولا تعمل في النظام المنعزل. جذبت محطات الطاقة الافتراضية الانتباه على مدار السنوات والعقود الماضية، وتم تنفيذ بعض محطات الطاقة الافتراضية عملياً مثل محطة Next Kraftwerke، ألمانيا. قد يكون لمحطات الطاقة الافتراضية مخطط تحكم مركزي أو موزع أو شامل. بناءً على مخطط التحكم، يتم تصميم تحسين / تشغيل محطة الطاقة الافتراضية. في هذا البحث، سيتم إجراء مسح شامل للأدبيات حول نماذج البرمجة الخطية الرئيسية المستخدمة لتحسين تشغيل محطات الطاقة الافتراضية. بعد ذلك، سيتم إنشاء نموذج شامل مصمم لتحسين محطات الطاقة الافتراضية يشتمل على مولدات قابلة للتشغيل والإيقاف ومولدات غير قابلة للتشغيل والإيقاف مع الأخذ بعين الاعتبار القيود الخطية لهذه المولدات والأجزاء بناءً على النماذج التي تمت دراستها في الأدبيات. بعد ذلك، سيتم تصميم أول نموذج لنظام تحسين لتقليل التكلفة التشغيلية وزيادة الأرباح أيضاً. بالإضافة إلى ذلك، سيتم النظر في عامل الخطر من خلال استخدام القيمة المشروطة في تمثيل المخاطر. بعد ذلك، سيتم تطوير قيود خطية لتحسين الأمان في توازن طاقة النظام واختبارها من أجل إثبات فاعليتها. باستخدام قيود الأمان هذه جنباً إلى جنب مع الأهداف السابقة، سيتم صياغة مشكلة تحسين متعددة الأهداف. يُقترح تضمين وحدة تحلية مياه كنوع حمل محدد نظراً لأهميتها خاصة في البلدان التي تعتمد بشكل كبير على تحلية المياه مثل المملكة العربية السعودية. تمتلك وحدات تحلية المياه بنية تحتية ضخمة ويمكن أن تكون بمثابة وحدات تخزين افتراضية. هذه الأسباب تجعل من الضروري للغاية النظر في مثل هذا النوع من الأحمال والنظر في طريقة تفاعله مع الشبكة الكهربائية. ستشارك محطات الطاقة الافتراضية في كل من: سوق اليوم التالي وسوق الموازنة الحالية. تم اقتراح نظام ARIMA محسن، كما سيتم اختبار نموذج SOS2 والذي يستخدم لتمثيل المعادلات الخطية متعددة الأجزاء الخطية في البرمجة الخطية. حيث أن التكلفة المتغيرة للمولد التقليدي يتم تمثيلها على هيئة دالة خطية متعددة الأجزاء. أخيراً،

تم اقتراح مفهوم "مجموعة محطات طاقة افتراضية" وتصميمه ومحاكاته واختباره كمفهوم جديد مقدم في هذا البحث
مشابهاً لمفهوم مجموعة الشبكات الصغيرة. سيكون للتصميم النهائي المقترح في هذا البحث موثوقية عالية للغاية بحيث
لا يفشل في موازنة الطاقة في أي ساعة من اليوم.

CHAPTER 1

INTRODUCTION

1.1 Background

In traditional networks, the load was assumed to be given and the supply had to be continuously adjusted. The units with the least production cost would cover the minimum load during the year and that can be easily illustrated on a load duration curve (LDC). In certain places, these units with the least energy production cost are usually the nuclear or coal fired units. The more expensive energy production units usually cover the peaks and renewable energy resources were not used as main sources that often. However, with the need for the reduction of CO₂ emission and for newer policies that help the world become greener, the urge of having more renewable energy resources and higher renewable energy resources penetration has risen. This requirement of variability of resources comes with network transformation, and different network topologies such as microgrids and virtual power plants (VPP). In Denmark and Germany for example, the renewable energy sources on some days would exceed the total demand and/or would exceed 50% of the total energy generation. If we take Germany as an example of a country whose energy demand has a peak around 80 GW, due to CO₂ reduction policies, it will phase out about 7GW of coal fired plants by 2022 in addition to 11 GW of nuclear power plants as well, [1]. We can notice the dramatic change in the resources types and structures. It is worth noting that not

only the generation resources are variable such as renewable energy sources (RES) but also the demand types such as electric vehicles (EV) and the network topologies are different, like distributed energy resources (DER) or distributed generation (DG). By 2030 and compared to 1990, the European Union (EU) is planning to reduce the greenhouse gases by 40% and to increase the renewable energy resources generation by up to 27%, [1]. Also, to avoid the climate change risks, 178 countries have signed Paris agreement which states that the global increase in temperature shall be reduced below 2 °C, [2].

The renewable energy sources (RES) are non-dispatchable unlike nuclear and coal powered sources. Therefore, the RES shall be treated differently to avoid wasting/curtailing their output. Such sources have both intermittent output as well as an output that cannot be dispatched whenever needed. There are challenges that come with the intermittency of those RES such as power quality, and voltage level control, but those challenges can be tackled with the use of the right technologies as stated in [3]. Due to the fact that those RES are non-dispatchable, the electricity market has to adjust its structure or strategy. In order to make the renewable energy sources competitive in the electricity market and to encourage the installation of renewable energy sources, policies like feed-in tariff have been made. But that has an effect on the profit of utilities. In [2][4], the authors stated that 10% penetration of photovoltaic (PV) resources has led to up to 15% drop in the profit of utilities in the US. The effect on the wholesale EU market is observable as well since the marginal cost of wind and solar is theoretically zero which causes a wholesale electricity price reduction, [5]. One of the methods that can be used to overcome the issue of dispatchability is to consider the load and the generation variable/flexible where both have

to be adjusted to meet each other. This helps in adjusting the demand based on the wholesale prices through what is called demand side management (DSM) or demand response (DR). Variable power plant is one idea that handles this concept of variable demand and variable supply.

RES penetration however can cause big loss to generators whose generation plants have high energy production cost as RES cause wholesale market price drop as illustrated in Figure 1-1. Though there are multiple issues that have been mentioned regarding the penetration of RES, the advancement in the communication technologies is making it easier now for the distribution and transmission operator to control the load in a way that can mitigate some of these issues. However, how to optimally dispatch these RES in a flexible manner with the flexible demand stays complicated with the current policies and market models. This is where VPP plays a role in transforming smart grids and RES into a more advanced model of interaction between the wholesale and retail markets. And that is done through the use of modern communication, control, and optimization technologies.

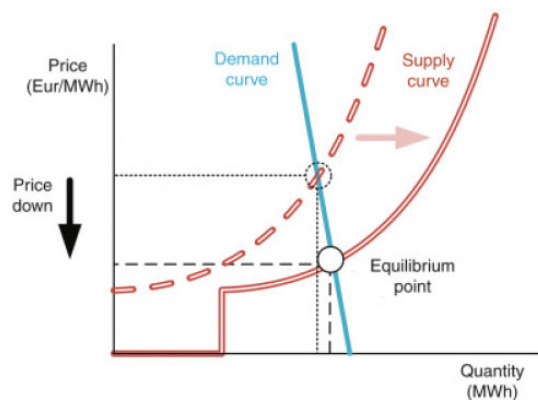


Figure 1-1 High penetration of DER into the Spot market [6].

There are a few VPPs that have been developed already by different entities and one of the most popular ones is Next Kraftwerke in Germany. Usually, those VPPs follow a centralized control scheme. Next Kraftwerke has more than 13,000 consumers and suppliers as participants in its VPP and their capacity exceeds 10,000 MW. Figure 1-2 shows that almost one third of the generation in Germany in 2016 was from renewable energy sources which shows why a VPP would be essential for areas like that. This of course does not apply to Germany only but a couple of other places too, for example: California, New York, Hawaii, Texas, Denmark, South Australia, Norway and Iceland. Figure 1-3 shows the same the energy generation in Germany in 2022. The results compared to Figure 1-2 show that there is great renewable energy sources penetration. As stated earlier, the RES participation into the wholesale market would lower the market price and that can be seen clearly in Figure 1-4.

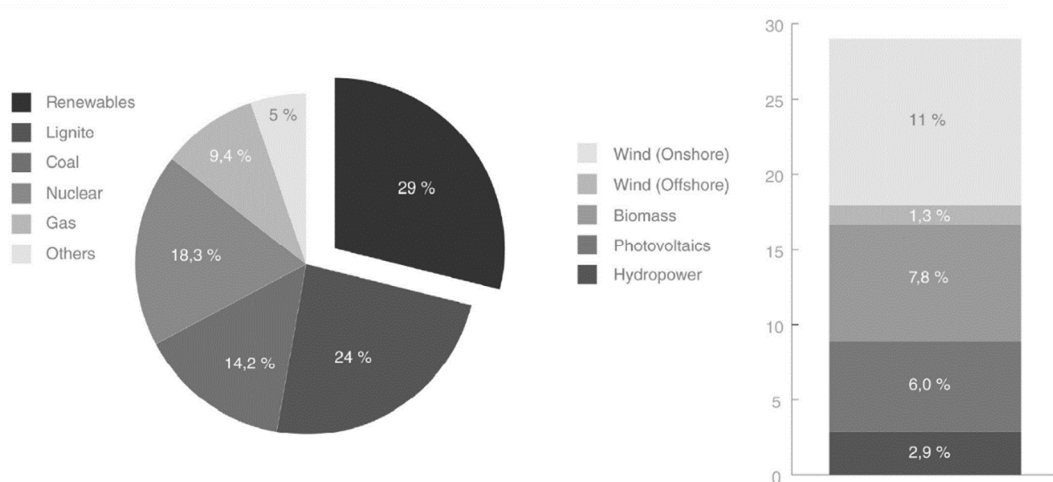
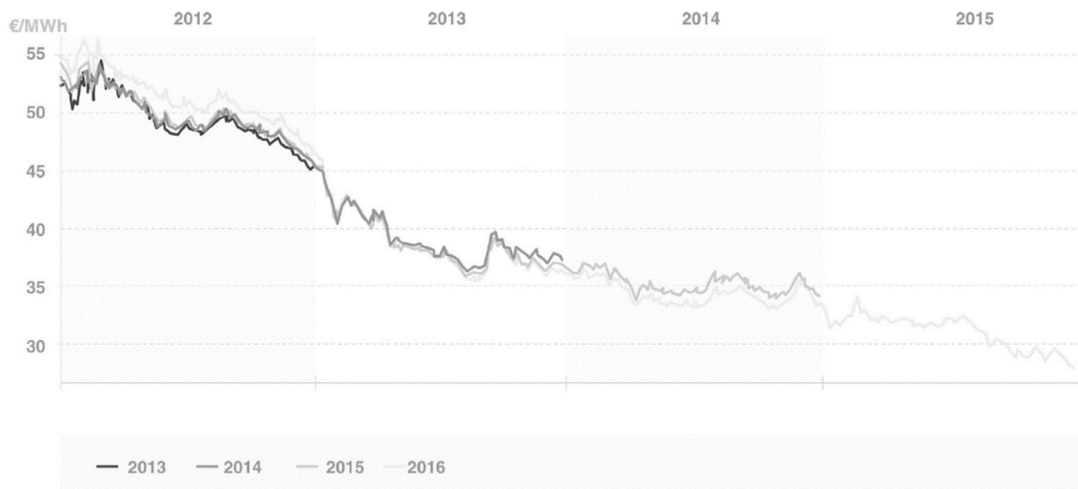
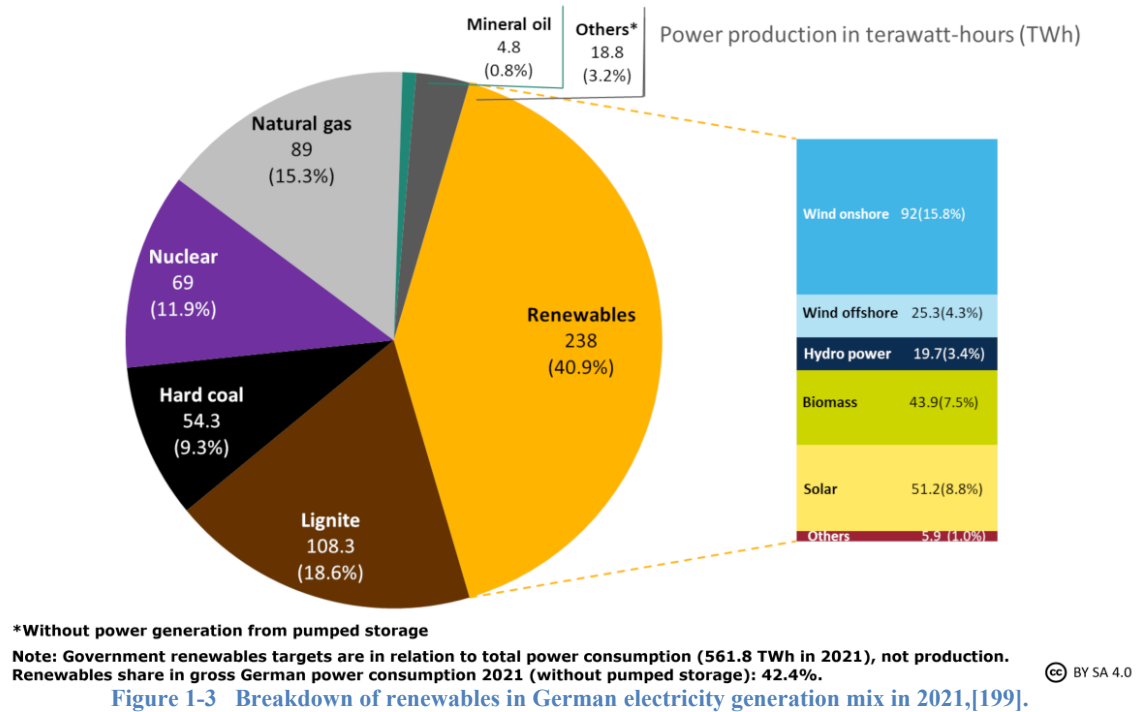


Figure 1-2 Breakdown of renewables in German electricity generation mix in 2016. Source: Next Kraftwerke, based on German Renewable Energies Agency 2016



As per [7], The inclusion of RES will lead to drop in the electricity prices based on which the sources with high energy production cost will be unprofitable. The authors estimated that through 2020, around 230 GW of the fossil resources capacity will be unprofitable in Europe.

1.2 Motivation

A VPP is the concept of managing multiple distributed energy resources (mainly renewable) in order to be represented as big power generator and thus help in the network power generation and to participate in the wholesale electricity market. The main difference between a microgrid (MG) and a VPP is that a MG can work in an islanded mode and it does not participate in the wholesale electricity market. The VPP participates in the wholesale electricity market and cannot be disconnected from the grid, [20]. From this, it can be concluded that the main purposes of having a VPP are:

1. Energy trading in the wholesale market
2. Generation and demand balancing
3. Network services
4. Optimization of the VPP consumption and generation.

VPP can be an aggregation of DER and that helps in:

1. Giving the DER the ability to enter the wholesale electricity market.
2. Having both the generation and load in one location.
3. Diversification of generation sources and locations.
4. Adding new ways of paying the renewable energy sources owners.

Though the most common applied VPP in practice is the centralized one, other schemes have various benefits but higher level of complexity. The three main control schemes are:

1. Centralized control method where the decision comes from the VPP operator.
2. Distributed control method where the generators have the choice to maximize their own profit and that might affect the overall competitiveness of the VPP in the

market. However, it would reduce the calculation burden compared to the centralized control. There is also a VPP communication control level.

3. Comprehensive control method. It is similar to the distributed control method but with multiple control points at the generators' side. Which means that there are multiple distributed control points that pass their best output to the central VPP to submit the overall strategic decision to the market.

Virtual Power plants have different control schemes among which some have advantages over others but also each has its own disadvantages. With that being said, there is a big area of research in the topic of VPP in terms of the technical aspect, commercial aspect, and optimization of objectives.

1.3 Objectives

The objectives of this research are:

1. To develop a model for the VPP which will contain both dispatchable and non-dispatchable generators.
2. To formulate the problem as a multi-objective optimization problem.
3. To assess and select an accurate and the most computationally efficient model for the conventional generator that will resemble the piecewise variable generation cost model.
4. To include specific type demand, a water desalination unit, into the VPP as this demand specifically plays an essential role into countries like Saudi Arabia that rely heavily onto desalination as a source of sweet water. In addition, the water

desalination unit can be used as a virtual energy storage unit in the planning of the VPP.

5. To develop a sequential ARIMA model for increased prediction accuracy for the real-time market data.
6. To propose, introduce and construct a new concept for a reliable VPP that is highly immune to power imbalance.
7. To construct a new concept of a VPP cluster. This VPP cluster will include an energy pool (EP) as part of its structure.

In order to achieve the above objectives, the following milestones/tasks shall be accomplished:

1. To make a thorough literature review on the major linear programming models of the VPP.
2. To make the most comprehensive model in terms of constraints based on the models studied in literature.
3. To formulate a single objective optimization problem to achieve operational cost minimization.
4. To make a single objective optimization problem in order to maximize the net profit.
5. The VPP model shall/will participate in the balancing and day-ahead markets.
6. Add the risk factor into the optimization problem.

1.4 Dissertation Organization

This dissertation starts with the introductory chapter which is the first one. The second chapter covers the literature work that has been done on the topic of virtual power plants, and its related areas. After that, the problem is formulated in the third chapter where multiple models are presented among which one is selected for the simulations. The fourth chapter explains the methodology used in this research while the fifth chapter has case studies and simulations of the selected virtual power plant. These simulations will be assessed and analyzed before introducing the idea of involving an energy pool with the VPP in the sixth chapter. The technique of using an energy pool with a virtual power plant will be introduced and a base case study will be simulated in the sixth chapter. After that, A virtual power plant cluster will be designed, its input data will be provided, and it will be simulated and analyzed in the seventh chapter. Lastly, the conclusion and possible future work will be provided over the last chapter.

CHAPTER 2

LITERATURE REVIEW

In this chapter, the definition and topologies of VPP will be presented and a review on the research done so far on VPPs will be made. Also, the applications of the different types of VPPs will be reviewed.

2.1 Virtual Power Plant

A VPP is a software platform that is based on the technologies of communication which integrate multiple distributed generation sources, and manages them along with energy storage systems and variable loads with the aid of Energy Management Systems (EMS), [8], [9]. To overcome the issues that come with the traditional DER such as the voltage level control, a VPP can be adopted, [10]-[12]. A VPP usually integrates and coordinates different DER into one single point which helps in both adding new benefits to the DER consumers and operators as well as eliminating/ easing issues that come with the DER such as stability [13]. There are a lot of concepts that apply to the smart grids that can also apply to VPPs such as web to energy [14]. Web to energy is a project to standardize information and communication technologies (ICT) in terms of network security, data base control, and communication. Thus, all market participants can have fair access to the same amount of information. New technologies in communication and concepts like Internet of Things (IoT) have enabled the operation of VPPs to be more efficient [15]. The idea of combining

multiple generation sources of different types under one virtual power plant has been assessed in [16] and several benefits have been given by the authors. Their proposed Virtual utility offers both the ability to participate in the wholesale market and the ability to have lower electricity prices. Their virtual utility was however not considered as a VPP without having the software and the structure that connects those DER to the grid as one big virtual power generator. This then helps the Transmission System Operator (TSO) to deal with the multiple DER as they are aggregated into one single point. The authors in [17] have divided the VPP into two types, where the first one is the Technical VPP (TVPP) and the second is the Commercial VPP (CVPP). The CVPP is responsible for the interaction between the wholesale market and the DER where it does the bidding, and balancing jobs without having to own the DER. On the other hand, the TVPP is responsible for the technical parameters of the VPP, sharing the necessary technical details with the TSO, including the physical structure of the VPP. It also covers the regulations segment of the VPP and its interaction with the network.

One of the necessary requirements for a well-designed VPP is using optimization techniques to handle the different objectives from the point of view of the TSO, VPP, DER owners, and the consumers. These optimization algorithms have been discussed and compared in [18]. With the increase of DER, and consumers turning into prosumers (consumers who have generators), the uncertainties have become more complicated to predict, and to have some statistics about the consumption, the authors in [19] proposed the use of Artificial Intelligence (AI) for the forecast purposes. In [20]-[21], different techniques of scheduling VPPs have been discussed. In [22], the authors have divided the

control methods of VPPs into three categories: centralized control where the VPP owner is the ultimate decision maker, and it sets the operating point for all participants, and they must follow. Thus, the optimization is done on the overall system with a large number of variables and uncertainties and this has two main issues. One of those issues is the computational burden and the other is the difficulty of inclusion of new participants. The second control method is the distributed control method where the central controller is responsible for the security and operation of the system while each DER has its own controller for subsystem optimization and this helps in allowing for system scalability. The third control method is the fully distributed control method which is very similar to the distributed control method but with less reliance on the central controller. In the third control method, the central controller becomes responsible for information exchange only. This method appears to be the best practice only in case the DER have the ability to respond to the market and system changes intellectually. Nevertheless, with the current network structure, it is very hard for the DER to make such intellectual and accurate optimization decisions in a well-coordinated manner.

In CVPP, the economic optimization issue is very complex and cannot easily be solved by deterministic approaches which urges the researchers to focus on the stochastic approximations. In [23], the different stochastic approximation methods for CVPP are discussed and compared. TVPP is responsible for the security of the participants of the VPP and the security of their information, and thus, the communication methods must be as secure as possible under the governance of the TVPP, [24]. A VPP solves the issue of intermittency of the RES by integrating multiple types of generators under one virtual

platform [25]. It also balances both the supply and the demand locally, and in the market which makes it promising for network operators, [26]-[27]. Other benefits that participants can make use of when being part of a VPP, as per [28]-[30], are profit maximization, which comes from the energy trading benefit. Also, the ability to participate in the balancing and network services.

A VPP can be thought of as an expanded and improved idea of a smart energy hub. A smart energy hub is considered as a zone where multiple generators and consumers are gathered in one hub with the use of network and communication technologies and they have their own control system, [31]. A smart energy hub also makes use of DSM where it helps both increasing the profit of the electricity providers and reducing the bills of the consumers, [32]. Expanding the idea of smart energy hub leads to the concept of VPPs. The VPP must work on maximizing the profit of all participants with the ability to help in network balancing services and having the least negative environmental impact, [18].

TVPP and CVPP cover all the technical and commercial aspects of the VPP and that includes the different feed in tariffs which are also a part of the EMS. These tariffs must be updated regularly and informed to consumers, [33]. Different ways of calculating these tariffs are provided in [34]. The authors in [35] propose information and communication technology for the communication between the VPP components. This highlights how essential the EMS to the VPP especially in terms of sizing optimization, [36].

2.2 Virtual Power Plant Components

As discussed earlier, a VPP contains both dispatchable and non-dispatchable generation units where the dispatchable units may include Combined Heat and Power (CHP), Plug-in Hybrid Electric Vehicle (PHEV), and Energy Storage Systems (ESS), [37]. The non-dispatchable units can be PV, Wind Turbines (WT), and Hydropower (HP). In addition to also including flexible loads under the category of demand response. Some references such as [38] and [39] study VPPs that are made of only one type of generators, which is WT in this case, and they study its participation in the intraday and day ahead markets. However, a more comprehensive study should cover different types of generators and loads. In [40], the authors consider only PV virtual power plant, and they proposed a distributed control method which also lacks the inclusion of multiple resources. In addition to the previous VPP components, the Information and Communication Technologies (ICT) are considered essential components of the VPP as well, [21]. EMS is one of the main components of the ICT, [41]. The EMS is utilized by the VPP to control and coordinate all the internal and external activities as well as the communication part, [37].

The authors in [42], study only non-dispatchable generators as part of the VPP while dispatchable sources are not considered. It is expected that by aggregating the separate DER into one VPP that can participate into the wholesale market that the total profit would increase according to [43],[44]. Considering the dispatchable generators adds a very important aspect to the VPP as they allow for the participation in the balancing market as well though this could come with the cost of extra CO₂ emission, [45],[46]. In [47], the authors include CHP as part of the dispatchable generates while [48] considers using ESS

with WT to make up for the uncertainty of the WT output. Thus, considering the ESS can mitigate the uncertainty of the non-dispatchable generators as per [49],[50]. In addition, the ESS by itself can be considered as a VPP and participate in the wholesale market, [51]. EVs can be integrated as a VPP if their size is sufficient enough and they can be a part of a VPP as well, [52]-[54]. A VPP may not only contain generators but also flexible loads under the category of demand response. These loads help in balancing the system as they can be optimized with the output of the intermittent resources, [55]-[57]. In [38] to [57], some authors consider one generator type such as wind or PV while others consider only one category of generators, dispatchable or non-dispatchable, some consider ESS, and some consider flexible loads. Nonetheless, none of them have considered combining all of these components in one system for a more comprehensive model of interaction between the different sources and load types.

2.3 Prediction Algorithms in VPP

In power systems, a number of mathematical methods/algorithms are used in forecasting. These methods can apply to VPPs as well since the components of a VPP are power systems components. In [58]- [60], energy management model method is implemented which aims for prediction accuracy improvement by the adjustment of the time scale. The authors in [61]-[63] proposed a model for a renewable energy market which has a stochastic nature. The proposed model is based on fuzzy logic and it is utilized often with WT models. Monte Carlo Simulation (MCS) is a good simulation method for solar radiation prediction, and it has been applied in [64]-[66] and they showed improvement in the prediction accuracy. A stochastic hybrid intelligent algorithm is employed in [67]-[69]

to predict the level of energy in the storage units which showed promising results in terms of balancing the energy and lowering the electricity prices. Another method is the empirical model and Artificial Neural Network (ANN) decomposition. This method was used in [70] and it has been proven to give better results compared to traditional methods in the diagnosis of faults in WT. ANN is a popular method which is implemented for optimization as well as prediction, and it helps in improving the computing efficiency in addition to the accuracy in prediction as per [71]-[73].

2.4 Uncertain Parameters

Uncertain parameters can be addressed through a different number of techniques. Some of these techniques are addressed here. One of the most popular techniques is Monte Carlo Simulation (MCS). It is used generally when there is a number of uncertain parameters. In [117], MCS was used to address the uncertainties in the renewable energy units output as well as the prices of the market. The same model was used in [118]-[120]. The normal distribution method (NDM) as used in [121] and [122] can also address those uncertain parameters which in return can help maximizing the profit. In [123] and [124] the Weibull distribution method was used to address the same three main uncertain parameters. One of the most popular models as well is the Auto Regressive Moving Average (ARMA) as used in [125]. ARMA was used in this paper in order address the uncertainty in the power production of a wind turbine. In [126], Point Estimate Method (PEM) was used. This method was used in [127] and [128] to model the uncertainty in a wind turbine power generation and the market prices. An extension to the PEM which is the two PEM was used

in [126] and [127] as well. When the volatility of the data does not have a specific distribution, the robust optimization method could be used as studied in [129]. In [130], the scenario tree method was adopted. It works by making a number of scenarios for a stochastic problem such as the problem with uncertain parameters. Each method of prediction of uncertain parameters has its advantages and drawbacks. ARIMA and MCS are however two of the most common methods used for prediction due to their effectiveness and strong mathematical theories and basis.

2.5 Optimization Algorithms in VPP

Optimization is the heart of the software part of any VPP as the objective functions for a VPP can vary and can be too many. Therefore, it is important to discuss the recent research onto the optimization of VPPs. In [34], [74], [75], the authors applied a method based on Ant Colony (AC) optimization method in order to prove that denser networks are not necessarily worse or less efficient. The authors have proven that the efficiency of the network rather improves the denser the network becomes; up to a certain point. A Mixed Integer Linear Method is used in [33], [35], [76] to forecast the wind speed and solar radiation. This method is rather a prediction method than an optimization one, but the authors considered the accuracy of the data as optimization to the output results. Genetic Algorithm (GA) is another heuristic search algorithm which has been applied in [77]-[79] to get the optimal sizing of multiple DER for an increase of the reliability of the system. In [80]-[83], Firefly (FF) optimization technique was employed to optimize the power lines loading for both the transmission and distribution systems for the most effective and

flexible loading condition. When it comes to DER placement and sizing, Artificial Bee Colony (ABC) is a good optimization method to use, [84]-[86]. Mixed Integer Linear Programming (MILP) has been utilized in [87]-[88] and obtained that the use of VPPs in networks help in increasing the reliability of the energy and in enhancing the economic feasibility of the system. Quantum Particle Swarm Optimization (QPSO) is an updated/improved model of the Particle Swarm Optimization (PSO) method,[89]-[91]. Optimal energy management of microgrids has been considered using PSO in [92]-[94] in a probabilistic framework. There are analytical methods such as the two thirds method, [105], or even better the upgraded form of it, [106]. The two thirds method has a drawback when the loads are not uniformly distributed and this is why the upgraded form of it was introduced. Linear programming as used in, [107], uses linear constraints to increase distributed generation penetration. When considering the variations of the renewable energy resources output over time, nonlinear programming could be used, [105]. There are also other methods such as dynamic programming and the heuristic methods. In [108], genetic algorithm was used for deciding the location and size of the power generating units under the constraints of the network. A similar purpose was served in [109] but using the firefly algorithm. In general, the optimization can be divided into two categories as per [103]. The first category is the optimization of the structure of the VPP. The second category is the optimization of the operation of the VPP. The operational optimization involves the constraints on the generation, charge and discharge of the battery, power flow limits and other technical limitations, [104].

In summary, there is a number of optimization techniques such as the one-dimensional optimization techniques such as Gauss Seidel which work only for objective functions of one variable only. Therefore, these are not suitable techniques for the purpose of this research. Multivariable objective model such as Newton's method have to be differentiable, continuous and they rely on initial conditions which also makes such methods not suitable for problems such as VPP optimization. Guided random or heuristic methods are popular and they can be used in VPP optimization problems. However, these techniques do not guarantee that the obtained solution is optimum. The solution could be a local minimum/ maximum. This makes linear programming models very appealing for VPP optimization problems especially that a VPP problem can be defined through linear set of constraints. A linear program that converges to an optimal solution, where the problem does not go infeasible or unbounded, guarantees an optimal solution. Therefore, mixed integer linear programming is selected as a balanced and powerful optimization technique among all the aforementioned techniques.

2.6 Electricity Market and VPPs

There are different markets for trading electricity. In fact, there are markets that are meant for supporting electrical services rather than electricity such as the frequency stability service. The main three markets are the day ahead market (DA), real time market (RT), and the ancillary service market (AS), [95], [110]. The DA market is the market where the bidding and offering are done for the next day. The prices of the DA market follow a probability distribution and there are a number of methods that address this uncertainty as

discussed in the previous sections. Point estimation method is one of those methods that can address the uncertainty in the prices of the DA market, [111]. Renewable energy sources have issues participating in those electricity markets namely: their limited capacity and their unstable output, [112]. To overcome this issue, the concept of a VPP is introduced, [113].

Participating in the DA market does not guarantee that the VPP will suffice its requirements. Therefore, there has to be a balancing market to make up for this. This is where the role of the RT market comes. The RT market is a market where the bids and offers are cleared on hourly basis. If a VPP for some reason is not able to satisfy the demand after the participation in the DA market, it can balance this by purchasing energy from the RT market, [114]. The last market of the three is the AS market. This is the market concerned about the security and stability of the electrical network. Therefore, services such as frequency balance, power balance and the compensation of reactive power are considered in the AS market. In addition, power quality concerns and voltage stability are part of this market too, [115]. The uncertainty of the prices causes a big burden on VPP owners when participating in the DA market. A big deviation from the forecasted prices or renewable energy sources output could lead to decrease in the expected profit or even big loss, [116].

To make a VPP to participate in these markets, a number of challenges are faced. These challenges can be technical, commercial, environmental, or regulatory. Overcoming these challenges or some of them can help in making the VPP feasible and profitable, [11], [102].

Market structure, forces, and prices are all commercial challenges. Some of the technical challenges are failures, maintenance and cyber security. Dispatchable units form an environmental challenge while forming regulatory entities is a regulatory challenge. Considering the DA or the RT market alone is not sufficient for VPP studies as any mismatch in the DA market can be covered in the RT market, and thus, a comprehensive model should consider both markets and should include different types of generators and loads.

2.7 Network Management Methods

The VPP is considered a network. Similarly, a microgrid (MG) is a network with some differences in terms of control/ management. Two more types are the load aggregator (LA) and the active distribution network (ADN). In this section, the control differences between those four types will be explained. First, in terms of objective, the VPP tries to maximize its profit, while a microgrid tries to stay stable while increasing the penetration of renewable energy sources, [131]-[138]. On the other hand, an ADN tries to have a stable power distribution and provide ancillary services when possible [139]-[146]. A load aggregator tries to make the maximum possible profit out of the load control [147]-[154]. In the four types, a controller shall be available. In a MG, and an ADN, the control scheme is centralized while it can be centralized or distributed in a LA. On the other hand, for a VPP, it can be centralized, distributed, or comprehensive. In terms of pricing, all the four systems are considered price takers which means that they offer/bid and wait for the clearing price of the market. Nevertheless, the VPP can be a price maker too.

2.8 Summary on VPP

The first point that is important to understand is why should a VPP be made. Figure 2-1 shows the objectives of a VPP. The term renewable distributed generation on the figure is referred to as (RDG). There are three main objectives, environmental, economic, and technical. Technically, the system shall be as reliable as possible. Also, voltage and power quality shall be maximized. This is in addition to preserving the technical constraints. Economically, the operational cost shall be minimized and the profit shall be maximized. Furthermore, the network losses shall be minimized which is part of the minimization of the operational cost and maximization of the profit. Environmentally, the whole world is going towards increasing the penetration of the renewable energy resources which also helps in reducing the emission of carbon dioxide.

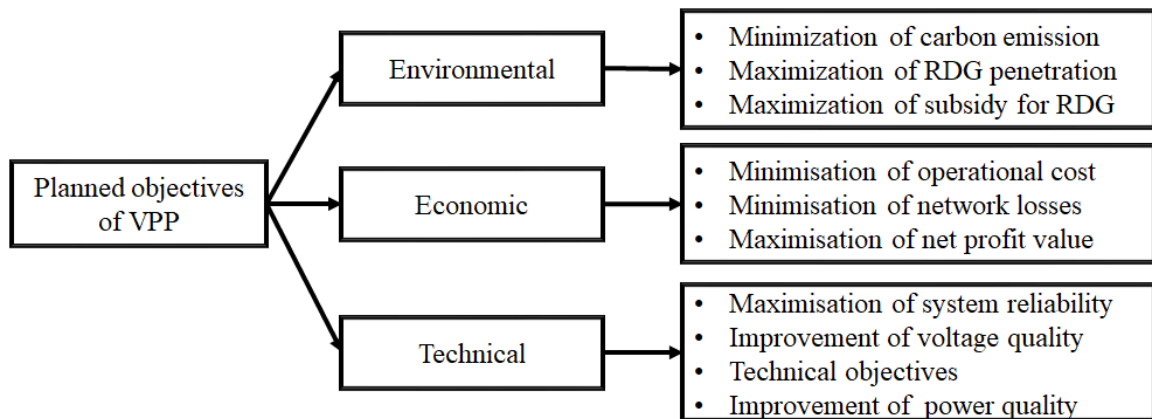


Figure 2-1 VPP objectives

In order to achieve these objectives, a number of challenges shall be overcome. These challenges are summarized in Figure 2-2. For example, with the introduction of the VPP, regulatory has to be made or the existing regulatory has to be adjusted to account for the introduction of this new system. The market prices are one of the most basic and biggest challenges to any participant in the electricity market. This is intensified where the market forces are considered. Dispatchable technologies can still be part of the VPP and they have an environmental impact that makes a new challenge for the VPP. Technically, there are some classical technical challenges such as outages, maintenance and failures. However, there are new challenges introduced with the introduction of smart grids and VPPs. A new challenge is the cyber security. This is because those systems rely heavily on the communication within the system and between different systems.

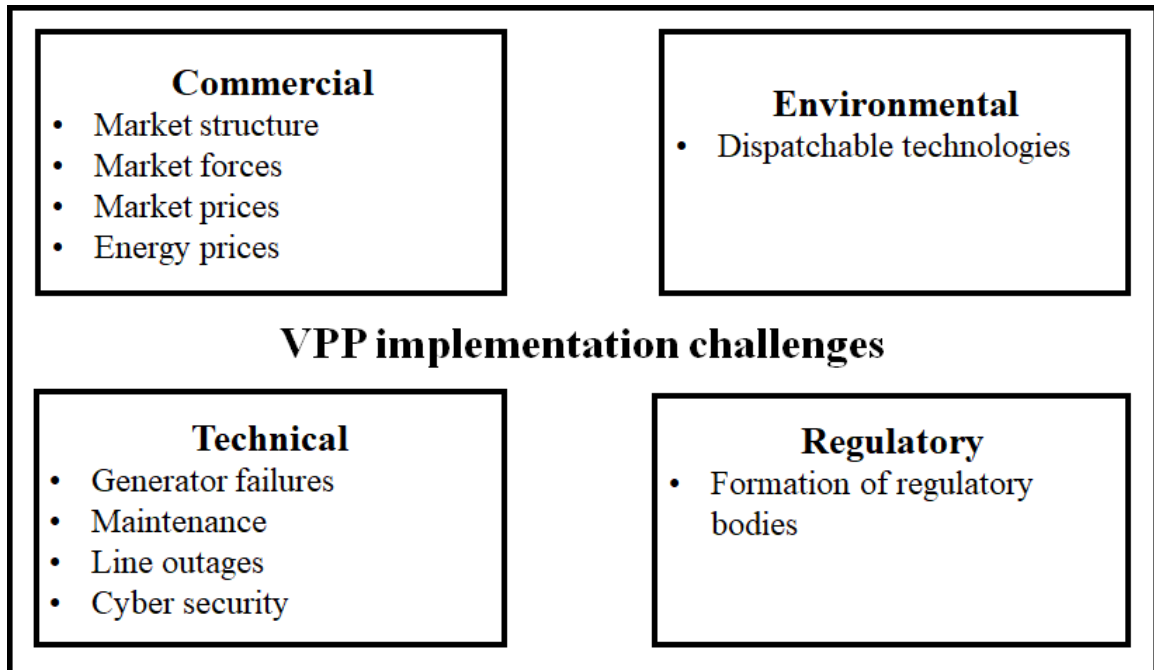


Figure 2-2 VPP implementation challenges

The VPP is beneficial in multiple ways. It benefits its owner or participants in terms of profit. It also benefits the system operator and policy maker as well as the environment since it will help reducing the emission of carbon dioxide. Whether the participant is a consumer or a supplier, both can benefit from being part of a VPP. This is summarized on Figure 2-3. To build the VPP, the architecture shown on Figure 2-4 is followed. First, forecast for the demand and renewable energy sources output shall be made. Second, stochastic optimization is run in order to decide the strategy of bidding, and scheduling of the virtual power plant. Third, the VPP communicates with both the operator of the market and the participants of the VPP in order to ensure no break in the technical requirements. This is all done through a controller which can be one of three types as shown on Figure 2-5.

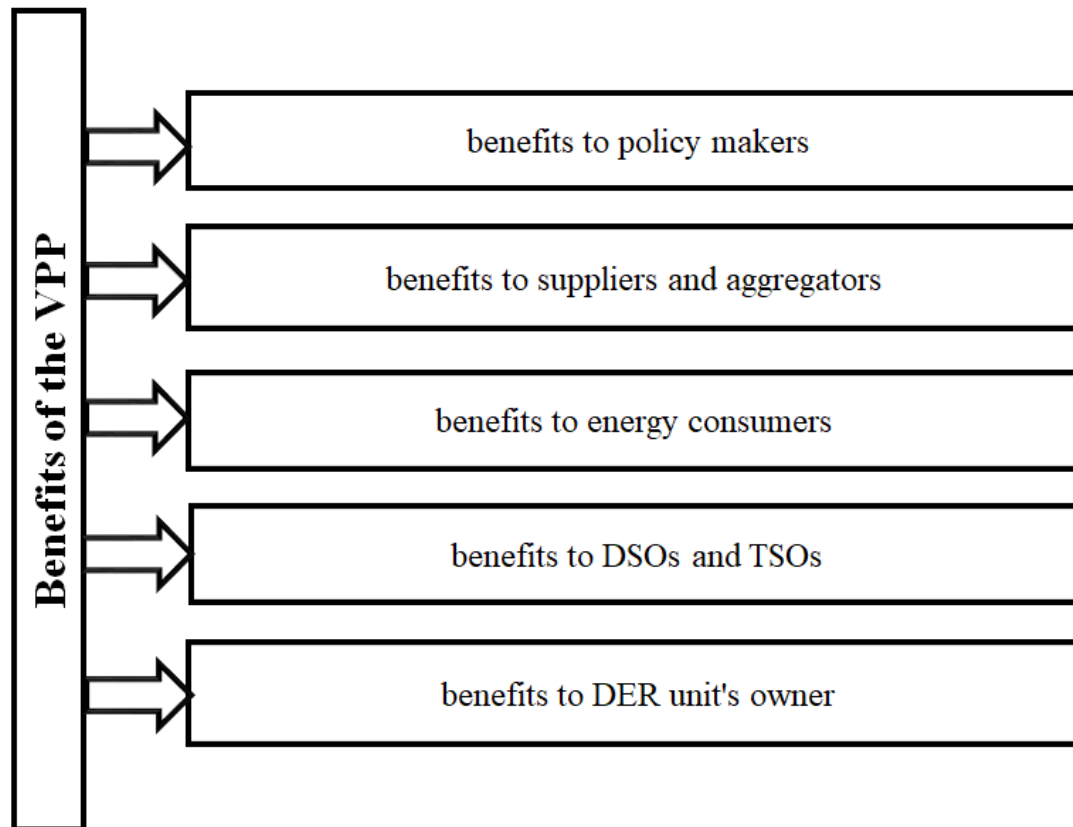


Figure 2-3 Benefits of the VPP

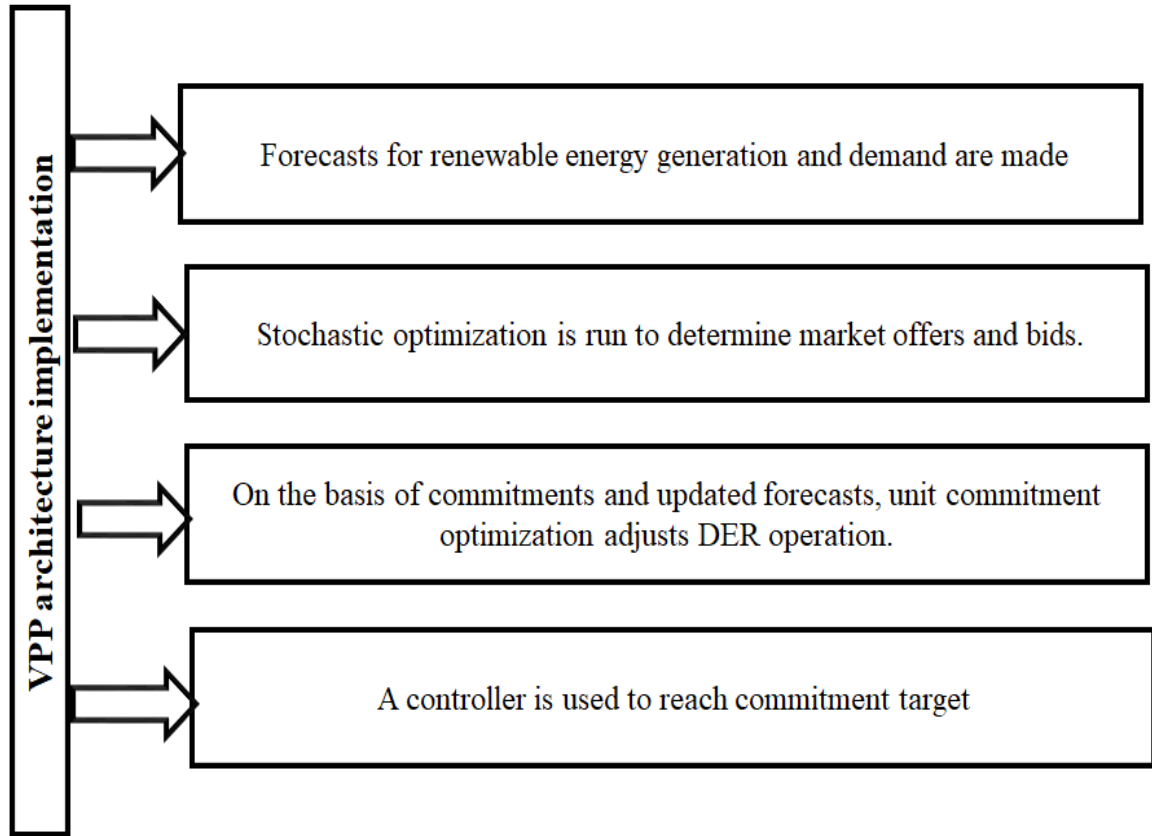


Figure 2-4 VPP architecture implementation

The controllers are three types mainly. The first is the centralized type where a central EMS controls the VPP. The EMS is in charge of all the units of the VPP where scheduling is done and communicated to the operator of the electricity market. The unit commitment is also under the control of the EMS in addition to the optimization of the system objectives in order to participate into the electricity markets. The central EMS also then communicates with the participants to inform them about their final commitment. On the other hand, in a distributed control, each participant has its own EMS and decides for its own profit. Those distributed EMS inform their schedules to the central EMS which then communicates with

the market operator. Lastly, a combination of those two control methods is the comprehensive control method.

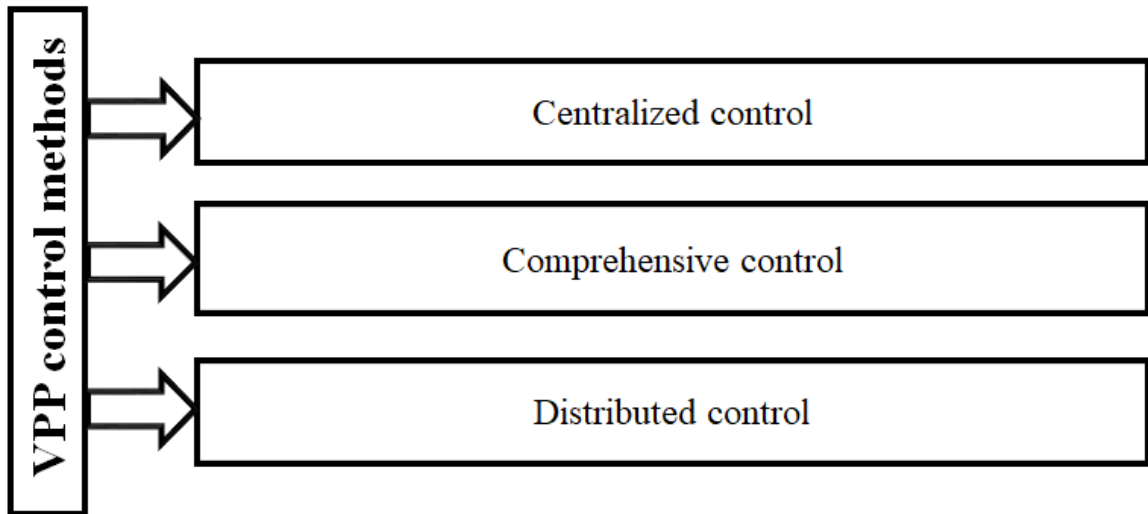


Figure 2-5 VPP control methods

To achieve the objectives of the VPP while facing the aforementioned challenges, optimization techniques are needed. Figure 2-6 shows the most popular but not all the optimization techniques that can be used for this purpose. Monte Carlo simulation can be used which is very useful for forecasting the uncertain parameters such as the output of the renewable energy sources. Robust optimization is also very important as it is a more conservative form of stochastic optimization which helps the VPP owner considering the worst-case scenario in the scheduling problem. There are many more techniques that can be used; some of which are mentioned on the figure below.

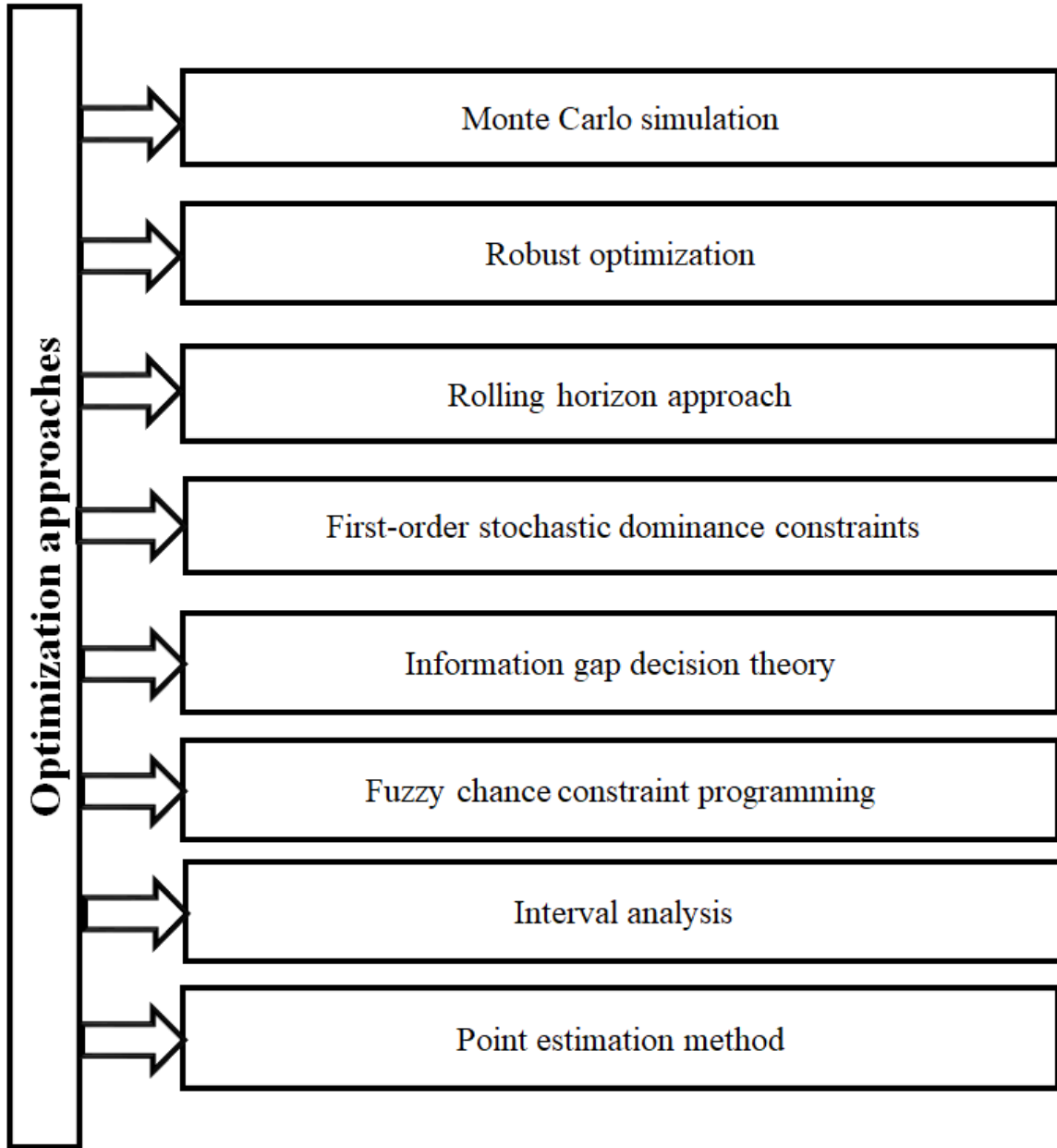


Figure 2-6 VPP optimization techniques

Since the optimization techniques consider forecasting data and uncertain parameters, it is important to define the uncertain parameters involved with the VPP. Figure 2-7 categorizes those uncertain parameters into three groups. Generator outages, unplanned outages and failures are all technical uncertain parameters. The demand and production can also

fluctuate for example when using renewable energy sources. The market and fuel prices are uncertain and they affect the operational cost and the profit directly. It is worth noting that some of these uncertain variables are direct inputs to the VPP model while others are not directly used as inputs to the VPP model. They are rather considered as risk factors.

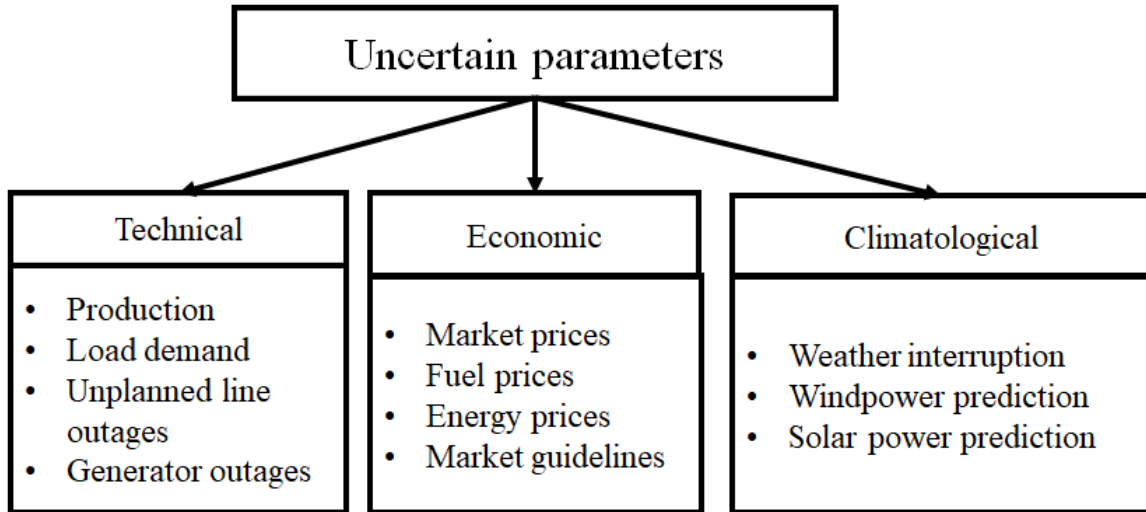


Figure 2-7 VPP uncertain parameters

Lastly, the VPP has two main parts. One is technical and one is commercial. Each ensures that no constraint will be broken and they also work towards the main objectives of the VPP. The technical part of the VPP which is referred to as TVPP monitors the technical parameters such as the voltage stability, system safety and a reliable connection between the DER and the grid. It is also responsible for maintenance and system monitoring as well as the balance of the system. Thus, any deviation from the schedule, for example in the DA market, shall be balanced in the RT market. Similarly, the commercial part of the VPP referred to as a CVPP has its own objectives. It is responsible for production and consumption forecast as well as the buying and selling services. The optimization,

calculation and scheduling that are used for trading in the market are all part of the tasks of the CVPP. This is shown on Figure 2-8.

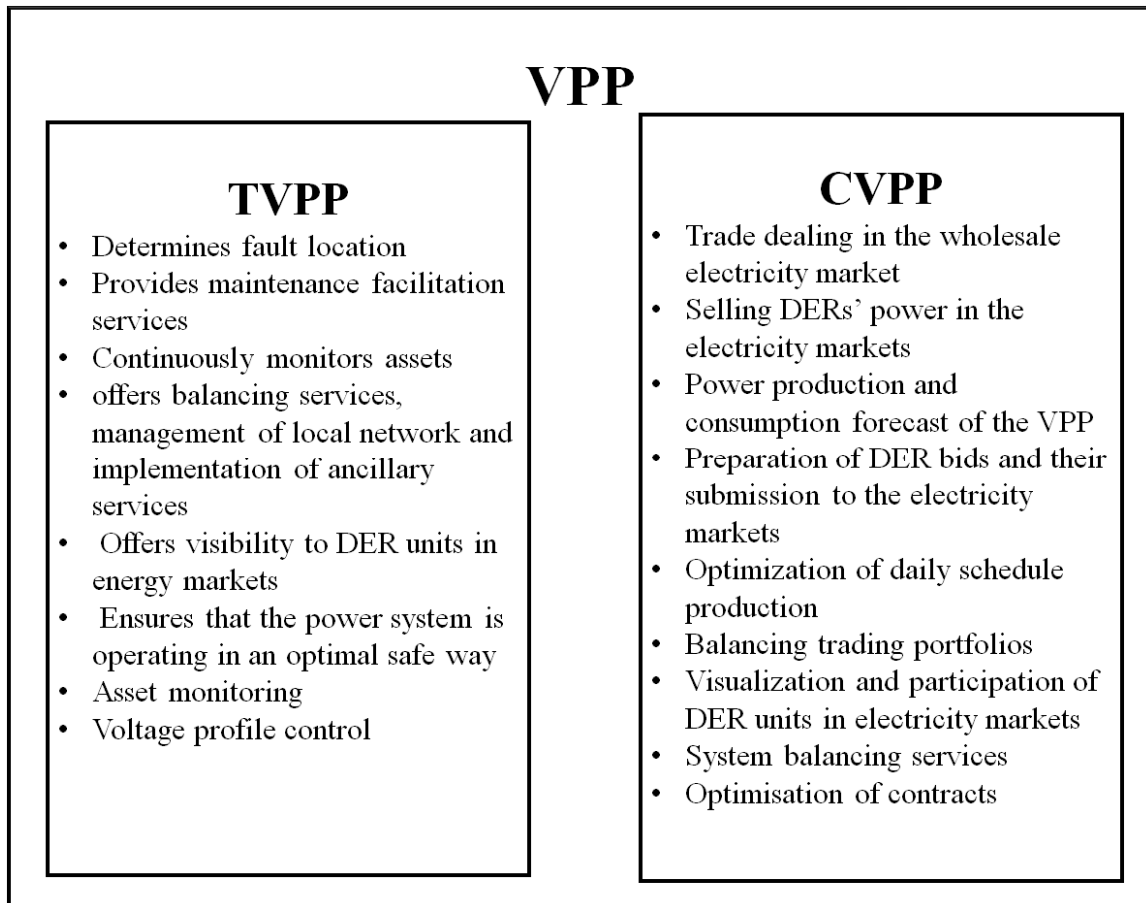


Figure 2-8 Technical and commercial VPP

CHAPTER 3

PROBLEM FORMULATION AND INPUT DATA

3.1 Virtual Power Plant Components Overview

A virtual power plant (VPP) is made up of a number of components. It includes stochastic renewable energy sources, energy storage units, conventional power plants, and demand. All of these components are interconnected through an electric network which is also considered in the operation of the VPP. For example, the lines power flow limits could affect the power transfer from the VPP to any demand existing on another node of the network.

Each of these components can be further classified to sub-components. For instance, the stochastic renewable energy sources can be wind turbines, solar cells, electric vehicles, etc. The demand can be flexible, semi-flexible, or inflexible. Conventional power plants can be diesel generators, combined cycle gas turbines, and so on. The most popular form of storage units is the battery. Nevertheless, other storage units can be considered too. The electric network itself can be further categorized into conventional network or smart grid.

The variables that are used in the research are divided into groups, namely: indexes, sets, parameters and variables. This notion is used as the majority of the coding of the equations

of the research will be done on General Algebraic Modeling System (GAMS). And GAMS requires the data to be divided into those categories. GAMS is a powerful software for linear programming problems. Based on the model, the problem could be a linear programming (LP) one and it could be mixed integer linear programming (MILP), nonlinear programming (NLP), or mixed integer nonlinear programming (MINLP).

3.2 The Electricity Markets

The electricity market has multiple trading floors including day ahead (DA) trading, and real time (RT) trading. In the DA market, as the name implies, the planning can be done one day ahead of the actual power delivery. It can also be done up to a few hours before. On the other hand, when it comes to the real-time market, just minutes before the actual power trading, it closes. The market has two main participants: suppliers/producers and consumers. This is aside from other regulatory participants. Based on the bid and ask prices which are ranked against each other as shown on Figure 3-1, the clearing price is decided. The clearing price is the price which the consumers need to pay to the producers for the quantity of power they will consume. The market considered in this research is New England Independent System Operator Market (ISO-NE). The ISO of New England, USA is responsible for all the planning, administration, contract management, and electricity markets of six states. Those six states are Massachusetts, Vermont, Connecticut, New Hampshire, Maine and Rhode Island. The state considered is Massachusetts. The data is collected for the city of Worcester, MA, USA which is considered the second most popular city in the state of MA after the city of Boston.

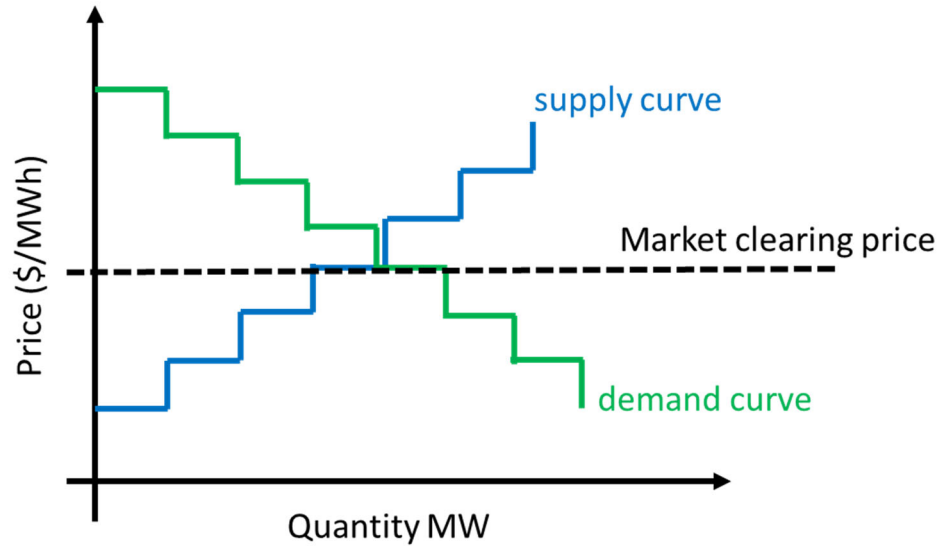


Figure 3-1 Ask/bid prices listing.

3.3 Virtual Power Plant and Energy Management System

Now as the idea of the VPP, its components, and the network is presented, it is important to elaborate on the operation of the VPP and then on the optimization of this operation. The VPP is governed by an energy management system (EMS). The EMS communicates with the network operator in a two-way communication channel in order to exchange both the technical and the commercial data. This data helps the VPP owner/controller to receive market data such as prices, and power transfer limits and helps the market operator balance the market between different parties. Figure 3-2, Figure 3-3, and Figure 3-4 elaborate more on the EMS operation with the VPP.

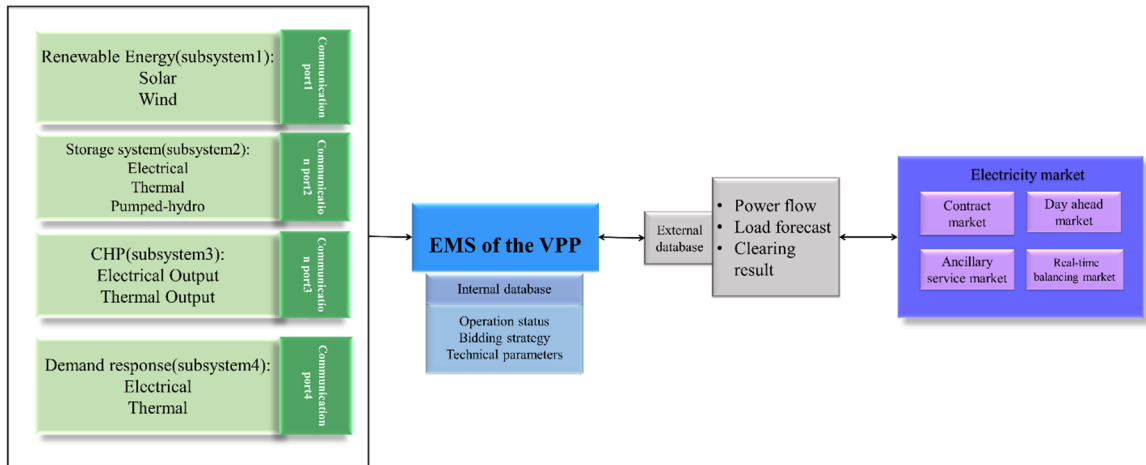


Figure 3-2 EMS operation with the VPP.

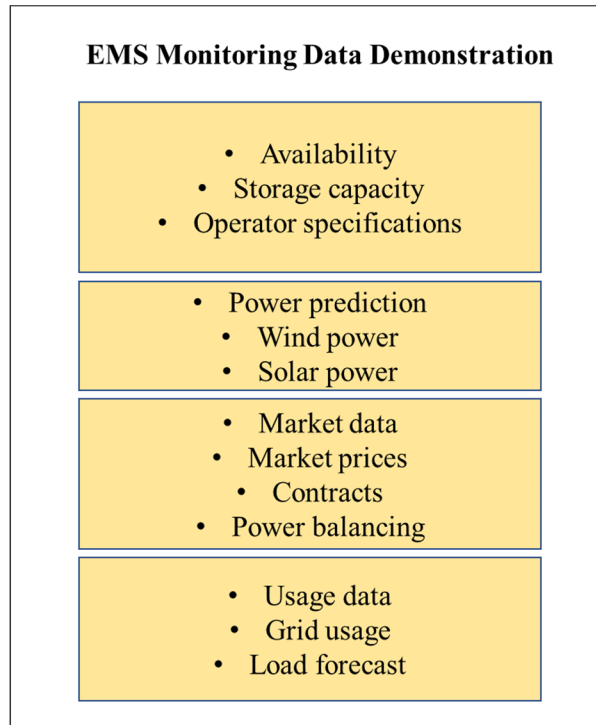


Figure 3-3 EMS monitoring data demonstration.

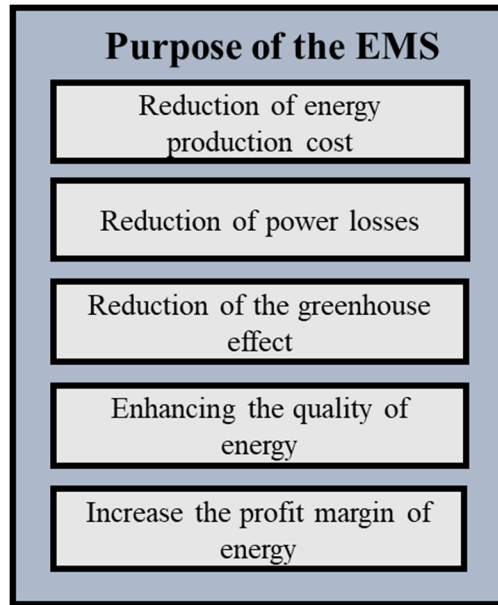


Figure 3-4 Purpose of the EMS.

3.4 Uncertainty and Decision Making

Due to the uncertainty of a number of parameters, stochastic modelling needs to be considered. There are different types of modelling for uncertain parameters. Before discussing the modelling methods of uncertain data, it must be noted that in stochastic modelling a limited set of realizations is made for each uncertain parameter. This has some disadvantages because it requires the availability of the data related to those realizations and the probability distribution of each of those uncertain parameters. With an increase into the number of scenarios in order to get the best possible output, this will definitely be computationally expensive. These scenarios or realizations can be made using several techniques some of which are shown on Figure 3-5.

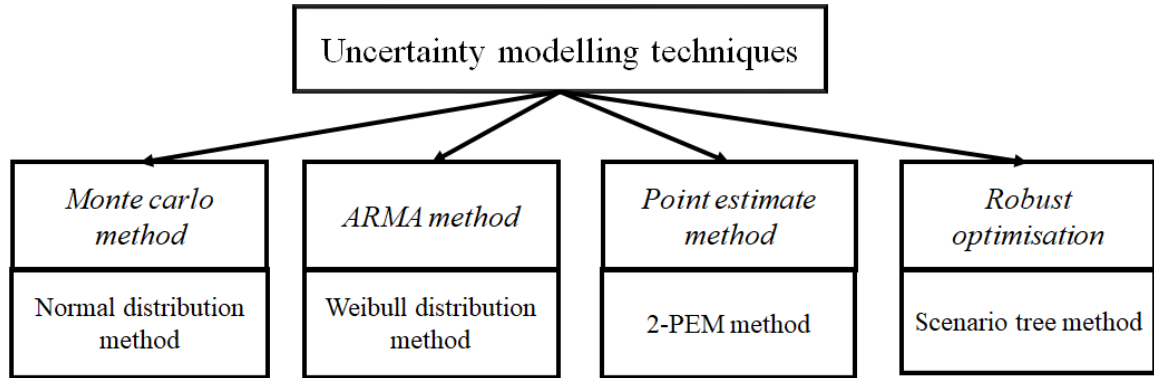


Figure 3-5 Uncertainty modelling techniques.

In robust optimization, the worst-case scenario is considered. In other words, all the possible scenarios are considered for each uncertain parameter. Then, the worst-case scenario is considered when optimizing (maximizing or minimizing) the objective function of the problem. By tuning some parameters, the decision maker may not go with the worst-case scenario but with less conservative results. This can best be explained by considering two types of robust optimization. The first type is the static robust optimization which considers the worst-case scenario as explained above and this is done by taking all decisions before making any scenario realization. The second is the two-stage robust optimization which in contrary to the first type allows some decisions to be made after some uncertainty realizations are made.

3.5 VPP Components

The VPP comprises multiple components which will be addressed in the sections below.

3.5.1 Demand

A VPP has demand units i.e., it has both generation and consumption units. These consumption units may be fed by the grid and may be fed by the sources of the VPP itself. The selection between the supply source depends on the market price and the maximum profit that can be made. For the best achievement of this objective, the demand has to be flexible which means that it can be partially shifted. The shifting can be based on the need; for example, due to the lack of the supply from the renewable energy units. It can also be due to the price of the market. Whenever the market price is high, the demand can be locally fed and when the price is low, it can be fed by the grid. The equations below represent the demand. It is worth noting that capital letters generally refer to sets or maximum and minimum limits. The detailed meaning of each symbol is shown on the list of abbreviations section.

$$\underline{p}_{dt}^D \leq p_{dt}^D \leq \overline{P}_{dt}^D, \forall d \in \Omega^D, \forall t \in \Omega^T \quad (3-1)$$

$$p_{dt}^D - p_{d(t-1)}^D \leq R_d^{D,U} \Delta t, \forall d \in \Omega^D, \forall t \in \Omega^T \quad (3-2)$$

$$p_{d(t-1)}^D - p_{dt}^D \leq R_d^{D,D} \Delta t, \forall d \in \Omega^D, \forall t \in \Omega^T \quad (3-3)$$

$$\sum_{t \in \Omega^T} p_{dt}^D \Delta t \geq \underline{E}_d^D, \forall d \in \Omega^D \quad (3-4)$$

Equation (3-1) shows that the demand at a point of time t shall be bounded by the maximum and minimum demand limit requirements. Equation (3-2) puts a limit on the rate of increase of demand over a period of time t while equation (3-3) puts a limit on the rate of decrease of demand over a period of time t . Lastly, equation (3-4) states that the summation of the energy demand of all points of time t shall be above the minimum demand level. It is worth noting that equation (3-1) shows that the demand is flexible, and it can be between two limits based on the requirement and planning. However, it can also address inflexible demand by considering that the maximum and minimum power limits are equal at a point of time t . The above equations form a linear set of constraints that can be used as a part of a linear program.

3.5.2 Conventional Generator

Conventional generators can be modelled by the equations below. This applies to conventional generators whether nuclear, combined cycle gas turbine, or others.

$$u_{ct}^C, v_{ct}^{C,SD}, v_{ct}^{C,SU} \in \{0,1\}, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-5)$$

$$u_{ct}^C - u_{c(t-1)}^C = v_{ct}^{C,SU} - v_{ct}^{C,SD}, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-6)$$

$$v_{ct}^{C,SU} + v_{ct}^{C,SD} \leq 1, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-7)$$

$$\underline{P}_c^C u_{ct}^C \leq p_{ct}^C \leq \overline{P}_c^C u_{ct}^C, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-8)$$

$$p_{ct}^C - p_{c(t-1)}^C \leq (R_c^{C,U} u_{c(t-1)}^C + R_c^{C,SU} v_{ct}^{C,SU}) \Delta t, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-9)$$

$$p_{c(t-1)}^C - p_{ct}^C \leq (R_c^{C,D} u_{ct}^C + R_c^{C,SD} v_{ct}^{C,SD}) \Delta t, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-10)$$

Equation (3-5) is a binary equation which lists the variables that can take a value of either zero or one. This will turn the problem to a mixed integer linear programming problem (MILP). Those three binary variables explain the status of the conventional generator: up and running, starting, or shutting down respectively. In addition, equations (3-6) and (3-7) bond a relation between those binary states. For example, the generator cannot be starting up and shutting down at the same time. Equation (3-8) points out the power generation limit of the generator with respect to its state. If the state is zero/off, then the power output shall be zero, and it shall be greater than zero otherwise. The last two equations, (3-9) and (3-10), restrict the ramping up and down of the generator respectively. Note that this ramping is tied with the status of the generator and with the ramping status. For instance, if the generator was up and running at time $t-1$, it cannot be starting up at time t . And thus, there is no starting up ramping but there can be ramping up while the generator is running.

3.5.3 Stochastic Renewable Energy Sources

The renewable energy resources are naturally intermittent and thus, the equation that governs them is concerned with the power being available or not being available. Thus, the power generation is between zero and the maximum output limit.

$$0 \leq p_{rt}^R \leq \bar{P}_{rt}^R, \forall r \in \Omega^R, \forall t \in \Omega^T \quad (3-11)$$

It is important to note that for demand, the main objective function can be cost minimization as the consumer is paying for supplying its demand. For the power generating units, the objective function would be maximizing the profit.

3.5.4 Energy Storage Units

Energy storage units are important when using renewable energy sources in order to cover up for their intermittent nature. When there is a surplus in the supply of the renewable energy sources, it can be stored in the batteries and when the power output of those renewable energy sources is low, it can be covered up by the discharge of the batteries. The following equations address the working behavior of the storage units.

$$u_{st}^S \in \{0,1\}, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-12)$$

$$0 \leq p_{st}^{S,C} \leq \bar{P}_{st}^{S,C} u_{st}^S, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-13)$$

$$0 \leq p_{st}^{SD} \leq \overline{P}_{st}^{S,D} (1 - u_{st}^S), \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-14)$$

$$e_{st}^S = e_{s(t-1)}^S + p_{st}^{S,C} \Delta t \eta_s^{S,C} - \frac{p_{st}^{S,D} \Delta t}{\eta_s^{S,D}}, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-15)$$

$$\underline{E}_{st}^S \leq e_{st}^S \leq \overline{E}_{st}^S, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-16)$$

The first binary variable states that the battery is either charging or discharging as it cannot be at both states at the same time. Equations (3-13) and (3-14) put limits on the charging and discharging processes of the battery respectively. Equation (3-15) shows the energy state of the battery considering the energy consumed/supplied by the discharge/charge. Equation (3-16) shows the limits on the energy state of the battery. For example, the energy might not be allowed to go below a specific state of charge (SOC) to avoid the degradation the battery's life.

3.5.5 Electric Network and Smart Grids

Each component of the VPP has been addressed separately, but when put together, they are part of an electric network. Thus, the network constraints must be considered such as the line flow limits. For simplicity, the power flow losses might be neglected. Therefore, the network model could be as below.

$$\sum_{g \in \Omega_n^G} p_{gt}^G - \sum_{(\ell|s(\ell)=n)} p_{\ell t}^L + \sum_{(\ell|r(\ell)=n)} p_{\ell t}^L = \sum_{d \in \Omega_n^D} p_{dt}^D, \forall n \in \Omega^N, \forall t \in \Omega^T \quad (3-17)$$

$$p_{\ell t}^L = \frac{1}{X_\ell} (\delta_{s(\ell)t} - \delta_{r(\ell)t}), \forall \ell \in \Omega^L, \forall t \in \Omega^T \quad (3-18)$$

$$-\bar{P}_\ell^L \leq p_{\ell t}^L \leq \bar{P}_\ell^L, \forall \ell \in \Omega^L, \forall t \in \Omega^T \quad (3-19)$$

$$\delta_{nt} = 0, n:\text{ref.}, \forall t \in \Omega^T \quad (3-20)$$

$$p_{gt}^G \in \Psi_{gt}^G, \forall g \in \Omega^G, \forall t \in \Omega^T \quad (3-21)$$

$$p_{dt}^D \in \Psi_{dt}^D, \forall d \in \Omega^D, \forall t \in \Omega^T \quad (3-22)$$

The nodal power balance is explained by equation (3-17) where the power going into the node (generated or received from the power lines) shall be equal to the power sent out to the power lines plus the power consumed by the demand at the node. Equations (3-18) and (3-19) define the amount of power on the network lines with respect to the power limits of the lines. The reference angle is set to zero at the reference node as per equation (3-20). Equations (3-21) and (3-22) define the generation and demand respectively in order to ensure that the battery is within the generation set while discharging and within the demand set while charging.

In all the models explained above, the simulation can be done ahead of time in order to plan the operation of the VPP. This is because the models rely on some known data and some uncertain data which are planned ahead of time. But what if some of this uncertain data becomes known before the planning horizon ends? This is actually the case with smart grids. When a two-way communication happens where the VPP and the grid exchange information, due to the availability of good communication technologies within the smart grid, both parties can utilize that while planning. For example, if the planning horizon is three hours, without communication systems, the VPP controller must plan the 3-hours horizon at once. If there is a good communication system, the controller has to plan the first hour only and the second hour can be planned based on the information available from the first hour which is communicated between the different parties within the smart grid. And the same thing applies to the 3rd hour of the planning horizon.

3.6 Optimal Scheduling

The main purpose of scheduling a virtual power plant is to decide what amount of energy to buy/sell at which point of time to maximize the overall profit. This is not a straightforward task as the parameters involved in the scheduling are not all certain. Some of the parameters that are uncertain are the energy price and the available power from the renewable energy resources. There are three ways to address these uncertainties. The first way is the deterministic way where the uncertain variables are represented with a single point forecast (one scenario). This makes the computation time at its minimum, generally. However, this method lacks accuracy. This is because any deviation from the single point forecast could change the results dramatically.

Therefore, another modelling method is the stochastic modelling. In stochastic modelling, every uncertain variable is represented with a certain number of scenarios. This usually gives better results compared to the deterministic modelling as it covers a wider range of feasible regions. Nevertheless, the actual scenario could still be outside of the region covered by the stochastic model. This is where the role of the third modelling technique comes. Robust optimization technique focuses on the worst-case scenario among all possible scenarios. This is the most conservative way to address an uncertain problem. The VPP owner can relax the conditions of the robust optimization if needed as per the available technical and commercial information. Robust optimization also guarantees the solution is feasible as it is considering the worst-case scenario and this is another advantage compared to stochastic modelling.

The modelling techniques apply to the energy traded in both the real-time (RT) and day ahead (DA) markets. Though most of the energy is traded in the DA market, the RT market must be considered in order to balance any mismatch from the DA market. The integration of the components of the VPP makes it challenging technically and commercially as there are many factors involved into the model. In addition, it must be noted that modelling a VPP using the aforementioned techniques could either consider risks and may not consider them. Considering risks can be addressed through the conditional value at risk (CVaR). The modelling will start by considering risk-ignorant model and later on, the risk factor could be considered.

Adaptive robust optimization is when stochastic optimization is merged with robust optimization. This is an evolved method from the two. Regardless to the method used, the decision making could be either be centralized using a central EMS and could be decentralized. In the centralized control method, the central EMS is the decision maker and it coordinates with both the system operator and with the local units in order to maximize the VPP profit. On the other hand, in the decentralized control scheme, the local units of the VPP have their own local EMS and they work to maximize their own profits separately. Then, the central EMS communicates with both the local units and the system operator to pass the economic information while ensuring no violation of the technical parameters.

3.6.1 Bidding Process

The scheduling process of the VPP passes through a sequence of steps which differ based on the market. This means that there should be flow of work for the DA market and flow of work for the RT market. As a start, it is easier to draw a timeline and start explaining the process of both the Day-ahead and real-time markets on it. The timeline is shown on Figure 3-6.

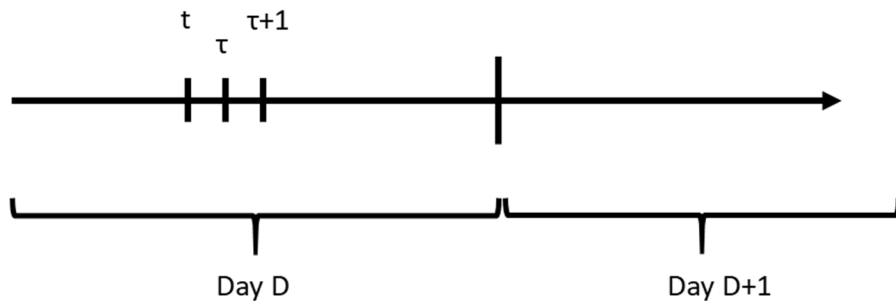


Figure 3-6 Day-ahead and real-time markets timeline

Let the timeline start at time t , on day D . The day ahead market bids one day ahead of time as the name suggests. Therefore, being on day D means we already know the schedule of the VPP for all the hours of day D for the DA market. However, we do not know the schedule of the virtual power plant in the real-time market for day D . So, at point t for example, the VPP operator wants to plan for the next DA market, day $D+1$. After all the information required is obtained from all components/participants of the virtual power plant, the EMS makes forecast for the next day market price. In addition, forecast is also made for the available power from the renewable energy resources. With this available information, the EMS of the VPP can now plan the bidding details for day $D+1$ in the DA market and shares this information with the market operator. Once the DA market closes, the VPP operator receives the final schedule and prices for day $D+1$. This is when the scheduling for the RT market starts.

Since we are at time t and the RT market works on hourly basis, the planning has to be done hour by hour continuously. This applies to day D and day $D+1$. Since we are at time t , the RT scheduling will be done for the next hour, call it τ . The EMS at this point knows almost for sure the available production from the renewable energy resources for time τ . This is because we are only few minutes away from time τ . The EMS also knows the DA schedule for day D in addition to the prices for the same market and same day. Based on this information, the EMS submits its schedule to the system operator and receives confirmation on the amount of power and price for that hour of the RT market. This process

continues until the scheduling horizon ends. The next timelines show the summary of the aforementioned processes for the Day-ahead and real-time market scheduling.

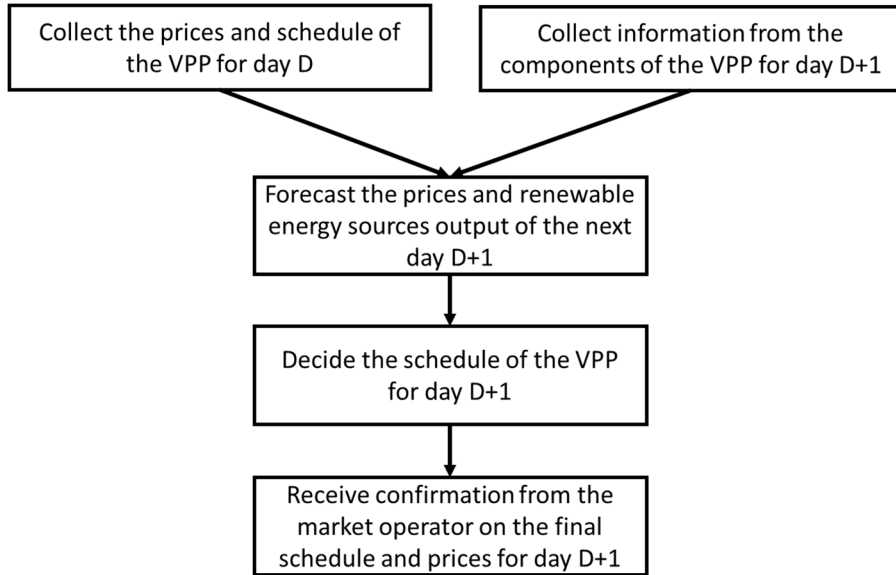


Figure 3-7 DA scheduling flowchart

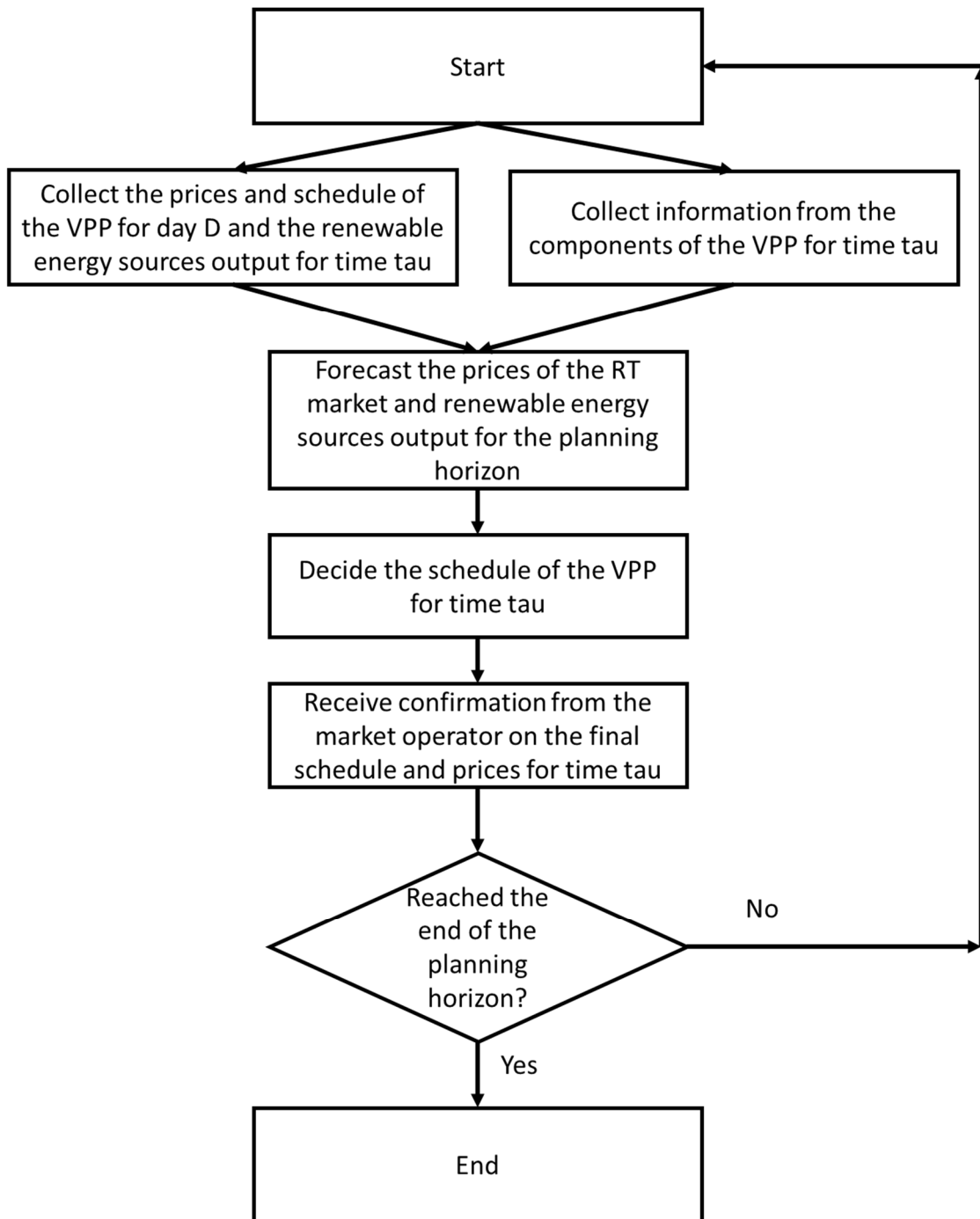


Figure 3-8 RT scheduling flowchart

3.7 Deterministic Model of the VPP

The first model discussed is the deterministic model where each parameter of the uncertain parameters is introduced as a single point. This model is governed by the equations presented in the sections below.

3.7.1 DA Market Deterministic Scheduling

The optimization problem is a MILP problem. The problem formulation shall account for all the components of the VPP and the network. Those components could be: conventional generator, renewable energy source, storage, and demand. The network has transmission lines, buses, and is connected to the electric network. The model should also account for the day-ahead and the real-time markets. Even though this section models the DA market, the RT market shall still be part of the forecast and planning in here. The objective function is the first equation which aims to maximize the profit from the Day-ahead and real-time markets. It also maximizes the utility of the demand. On the other hand, it minimizes the generator running cost, and the ramp up and ramp down costs.

Equation (3-24) is the nodal power balance at the busses connected to the electric network while equation (3-25) is the nodal power balance at the buses that are not connected to the electric network. Equation (3-26) states that the power traded in the day-ahead and real-time markets shall be equal to the power exchanged through the main grid. Equations (3-27) and (3-28) calculate the power flow over the lines and sets them within the technical limits respectively. After that, the voltage angle of the reference bus is set to zero while the

angles at the other busses are calculated accordingly. Then, the power traded in the DA market alone or in both the Day-ahead and real-time markets together cannot exceed the lower and higher limits of the capacity of the VPP.

Next, the power exchange limits with the main grid are set. The minimum daily energy requirement of the demands of the VPP is also set and this addresses the first constraint on the first component of the VPP which is the demand. The demand is then set within the maximum and minimum limits and the demand ramp up and down limits are also outlined. After that, the equations governing the conventional generator are provided. Similar to the demand, there are limits on the generation, ramp up and ramp down of the generator. It is worth noting that the first binary variable is introduced in the power limits equation of the conventional generator and it represents the status of the generator as on or off. The next group of equations govern the startup and shut down cost of the conventional generator. There are auxiliary variables introduced in these equations and they help with the purpose of including the startup and shut down costs in the objective function. For example, if the startup cost is included in the objective function without the help of the auxiliary variable, it might give wrong results because the conventional generator might not run at all or might not be running at time t . Thus, an auxiliary variable helps ensuring that the startup and shut down costs will not be included in the objective function if the generator did not start up or shut down at time t .

The last two elements are the storage units and the renewable energy units. The storage unit is represented by five equations stating the state of charge, maximum and minimum

states of charge, discharging limits, charging limits and the total power produced/consumed by the storage unit. Lastly, the power produced by the renewable energy source is limited by upper and lower boundaries. It must be noted that the uncertain parameters are represented by a single point forecast in this model. This is apparent from the objective function which has a fixed forecasted price for the Day-ahead and real-time markets denoted by λ_t^{DA} and λ_t^{RT} . The same thing applies to the last equation which governs the renewable energy units' output and represents their output by a single point forecast.

$$\begin{aligned} \max_{\Phi^{\text{DA}}} \sum_{t \in \Omega^{\text{T}}} \left[\lambda_t^{\text{DA}} p_t^{\text{DA}} \Delta t \right. \\ \left. + \lambda_t^{\text{RT}} p_t^{\text{RT}} \Delta t + \sum_{d \in \Omega^{\text{D}}} U_{dt}^{\text{D}} p_{dt}^{\text{D}} \Delta t - \sum_{c \in \Omega^{\text{C}}} (C_c^{\text{C,V}} p_{ct}^{\text{C}} \Delta t + \bar{c}_{ct}^{\text{C}} + \underline{c}_{ct}^{\text{C}}) \right] \end{aligned} \quad (3-23)$$

$$\begin{aligned} \sum_{c \in \Omega_n^{\text{C}}} p_{ct}^{\text{C}} + \sum_{r \in \Omega_n^{\text{R}}} p_{rt}^{\text{R}} + \sum_{s \in \Omega_n^{\text{S}}} p_{st}^{\text{S}} - \sum_{\ell | s(\ell)=n} p_{\ell t}^{\text{L}} + \sum_{\ell | r(\ell)=n} p_{\ell t}^{\text{L}} = p_{nt}^{\text{M}} + \sum_{d \in \Omega_n^{\text{D}}} p_{dt}^{\text{D}}, \forall n \\ \in \Omega^{\text{M}}, \forall t \in \Omega^{\text{T}} \end{aligned} \quad (3-24)$$

$$\begin{aligned} \sum_{c \in \Omega_n^{\text{C}}} p_{ct}^{\text{C}} + \sum_{r \in \Omega_n^{\text{R}}} p_{rt}^{\text{R}} + \sum_{s \in \Omega_n^{\text{S}}} p_{st}^{\text{S}} - \sum_{\ell | s(\ell)=n} p_{\ell t}^{\text{L}} + \sum_{\ell | r(\ell)=n} p_{\ell t}^{\text{L}} = \sum_{d \in \Omega_n^{\text{D}}} p_{dt}^{\text{D}}, \forall n \\ \in \Omega^{\text{N}} \setminus n \in \Omega^{\text{M}}, \forall t \in \Omega^{\text{T}} \end{aligned} \quad (3-25)$$

$$p_t^{\text{DA}} + p_t^{\text{RT}} = \sum_{n \in \Omega^{\text{M}}} p_{nt}^{\text{M}}, \forall t \in \Omega^{\text{T}}, \quad (3-26)$$

$$p_{\ell t}^{\text{L}} = B_{\ell}(\delta_{s(\ell)t} - \delta_r(\ell)t), \forall \ell \in \Omega^{\text{L}}, \forall t \in \Omega^{\text{T}} \quad (3-27)$$

$$-\bar{P}_\ell^L \leq p_{\ell t}^L \leq \bar{P}_\ell^L, \forall \ell \in \Omega^L, \forall t \in \Omega^T \quad (3-28)$$

$$\delta_{nt} = 0, n: \text{ref.}, \forall t \in \Omega^T, \quad (3-29)$$

$$-\pi \leq \delta_{nt} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \in \Omega^T \quad (3-30)$$

$$\underline{P}^V \leq p_t^{\text{DA}} \leq \bar{P}^V, \forall t \in \Omega^T \quad (3-31)$$

$$\underline{P}^V \leq p_t^{\text{DA}} + p_t^{\text{RT}} \leq \bar{P}^V, \forall t \in \Omega^T, \quad (3-32)$$

$$-\bar{P}_n^M \leq p_{nt}^M \leq \bar{P}_n^M, \forall n \in \Omega^M, \forall t \in \Omega^T, \quad (3-33)$$

$$\sum_{t \in \Omega^T} p_{dt}^D \Delta t \geq \underline{E}_d^D, \forall d \in \Omega^D, \quad (3-34)$$

$$\underline{P}_{dt}^D \leq p_{dt}^D \leq \bar{P}_{dt}^D, \forall d \in \Omega^D, \forall t \in \Omega^T, \quad (3-35)$$

$$-R_d^{\text{D,D}} \Delta t \leq p_{dt}^D - p_{d(t-1)}^D \leq R_d^{\text{D,U}} \Delta t, \forall d \in \Omega^D, \forall t \in \Omega^T \quad (3-36)$$

$$\underline{P}_c^C u_{ct}^C \leq p_{ct}^C \leq \bar{P}_c^C u_{ct}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \quad (3-37)$$

$$-R_c^{\text{C,D}} \Delta t \leq p_{ct}^C - p_{c(t-1)}^C \leq R_c^{\text{C,U}} \Delta t, \forall c \in \Omega^C, \forall t \in \Omega^T, \quad (3-38)$$

$$\bar{c}_c^C(u_{ct}^C - u_{c(t-1)}^C) \leq \bar{c}_{ct}^C, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-39)$$

$$0 \leq \bar{c}_{ct}^C, \forall c \in \Omega^C, \forall t \in \Omega^T \quad (3-40)$$

$$\underline{c}_c^C(u_{c(t-1)}^C - u_{ct}^C) \leq \underline{c}_{ct}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \quad (3-41)$$

$$0 \leq \underline{c}_{ct}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \quad (3-42)$$

$$e_{st}^S = e_{s(t-1)}^S + \eta_s^{S,C} p_{st}^{S,C} \Delta t - \frac{p_{st}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-43)$$

$$\underline{E}_s^S \leq e_{st}^S \leq \bar{E}_s^S, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-44)$$

$$0 \leq p_{st}^{S,D} \leq \bar{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-45)$$

$$0 \leq p_{st}^{S,C} \leq \bar{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-46)$$

$$p_{st}^S = p_{st}^{S,D} - p_{st}^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T \quad (3-47)$$

$$0 \leq p_{rt}^R \leq P_{rt}^{R,A}, \forall r \in \Omega^R, \forall t \in \Omega^T \quad (3-48)$$

Note that by solving this optimization problem, the scheduling in terms of quantity and price for both the Day-ahead and real-time markets will be done. Thus, the EMS of the VPP will be able to submit the bids and offers for the planning horizon for both the DA and the RT markets. However, the VPP operator will apply only for the DA market and the RT market will be optimized separately after the output results of the DA market are provided. Noting that Φ^{DA} represents the set that comprises all the variables to be optimized in the DA market.

3.7.2 RT Market Deterministic Scheduling

Once the DA scheduling is done as per the previous section, the RT market scheduling starts. It can be noticed that the equations are very much similar. The first main difference is that the RT market scheduling will start from time τ . Thus, the DA term will be removed from the objective function. Wherever the power delivered to the DA market is mentioned, it will have a sign ' $\sim$ ' above it to state that this has become an actual value and not an estimate anymore. Also, the equation governing the power exchange limit in the day-ahead market will be removed since the DA market scheduling is done. In equation (3-59), the demand is split into two time periods. The time period where the demand is known by now and the time period after point τ . Lastly, the renewable energy source output will be made into two equations and this is because the output of the renewable energy source at time τ which is right after the day-ahead market closes and right before the real-time market scheduling starts is known.

$$max_{\Phi^{RT}} \sum_{t \in \tau} \left[\lambda_t^{RT} p_t^{RT} \Delta t + \sum_{d \in \Omega^D} U_{dt}^D p_{dt}^D \Delta t - \sum_{c \in \Omega^C} (C_c^{C,V} p_{ct}^C \Delta t + \bar{c}_{ct}^C + \underline{c}_{ct}^C) \right] \quad (3-49)$$

$$\sum_{r \in \Omega_n^R} p_{rt}^R + \sum_{s \in \Omega_n^S} p_{st}^S - \sum_{\ell | s(\ell)=n} p_{\ell t}^L + \sum_{\ell | r(\ell)=n} p_{\ell t}^L = p_{nt}^M + \sum_{d \in \Omega_n^D} p_{dt}^D, \forall n \in \Omega^M, \forall t \geq \tau \quad (3-50)$$

$$\sum_{r \in \Omega_n^R} p_{rt}^R + \sum_{s \in \Omega_n^S} p_{st}^S - \sum_{\ell | s(\ell)=n} p_{\ell t}^L + \sum_{\ell | r(\ell)=n} p_{\ell t}^L = \sum_{d \in \Omega_n^D} p_{dt}^D, \forall n \in \Omega^N \setminus n \quad (3-51)$$

$$\in \Omega^M, \forall t \geq \tau$$

$$\hat{p}_t^{DA} + p_t^{RT} = \sum_{n \in \Omega^M} p_{nt}^M, \forall t \geq \tau, \quad (3-52)$$

$$p_{\ell t}^L = B_{\ell}(\delta_{s(\ell)t} - \delta_{r(\ell)t}), \forall \ell \in \Omega^L, \forall t \geq \tau \quad (3-53)$$

$$-\bar{P}_{\ell}^L \leq p_{\ell t}^L \leq \bar{P}_{\ell}^L, \forall \ell \in \Omega^L, \forall t \geq \tau \quad (3-54)$$

$$\delta_{nt} = 0, n: \text{ref.}, \forall t \geq \tau \quad (3-55)$$

$$-\pi \leq \delta_{nt} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \geq \tau \quad (3-56)$$

$$\underline{P}^V \leq \hat{p}_t^{DA} + p_t^{RT} \leq \bar{P}^V, \forall t \geq \tau \quad (3-57)$$

$$-\bar{P}_n^M \leq p_{nt}^M \leq \bar{P}_n^M, \forall n \in \Omega^M, \forall t \geq \tau, \quad (3-58)$$

$$\sum_{t=1}^{\tau-1} \tilde{p}_{dt}^D \Delta t + \sum_{t=\tau}^{|\Omega^T|} p_{dt}^D \Delta t \geq \underline{E}_d^D, \forall d \in \Omega^D, \quad (3-59)$$

$$\underline{P}_{dt}^D \leq p_{dt}^D \leq \bar{P}_{dt}^D, \forall d \in \Omega^D, \forall t \geq \tau, \quad (3-60)$$

$$-R_d^{D,D} \Delta t \leq p_{dt}^D - p_{d(t-1)}^D \leq R_d^{D,U} \Delta t, \forall d \in \Omega^D, \forall t \geq \tau \quad (3-61)$$

$$\underline{P}_c^C u_{ct}^C \leq p_{ct}^C \leq \bar{P}_c^C u_{ct}^C, \forall c \in \Omega^C, \forall t \geq \tau, \quad (3-62)$$

$$-R_c^{C,D} \Delta t \leq p_{ct}^C - p_{c(t-1)}^C \leq R_c^{C,U} \Delta t, \forall c \in \Omega^C, \forall t \geq \tau, \quad (3-63)$$

$$\bar{C}_c^C (u_{ct}^C - u_{c(t-1)}^C) \leq \bar{c}_{ct}^C, \forall c \in \Omega^C, \forall t \geq \tau \quad (3-64)$$

$$0 \leq \bar{c}_{ct}^C, \forall c \in \Omega^C, \forall t \geq \tau \quad (3-65)$$

$$\underline{C}_c^C (u_{c(t-1)}^C - u_{ct}^C) \leq \underline{c}_{ct}^C, \forall c \in \Omega^C, \forall t \geq \tau, \quad (3-66)$$

$$0 \leq \underline{c}_{ct}^C, \forall c \in \Omega^C, \forall t \geq \tau, \quad (3-67)$$

$$e_{st}^S = e_{s(t-1)}^S + \eta_s^{S,C} p_{st}^{S,C} \Delta t - \frac{p_{st}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \geq \tau \quad (3-68)$$

$$\underline{E}_s^S \leq e_{st}^S \leq \bar{E}_s^S, \forall s \in \Omega^S, \forall t \geq \tau \quad (3-69)$$

$$0 \leq p_{st}^{S,D} \leq \bar{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \geq \tau \quad (3-70)$$

$$0 \leq p_{st}^{S,C} \leq \bar{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau \quad (3-71)$$

$$p_{st}^S = p_{st}^{S,D} - p_{st}^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau \quad (3-72)$$

$$0 \leq p_{rt}^R \leq \tilde{P}_{rt}^{R,A}, \forall r \in \Omega^R, \forall t = \tau \quad (3-73)$$

$$0 \leq p_{rt}^R \leq P_{rt}^{R,A}, \forall r \in \Omega^R, \forall t > \tau \quad (3-74)$$

Thus, the information known at the beginning of the RT market are: the schedule of the DA market (price and quantity), the renewable energy output at time τ and the prices of the time periods of the RT market that have come before the point τ . Based on this, the planning for the RT market will be done step by step for every step of time (say every hour).

3.8 Stochastic Scheduling of the VPP

For more accurate modelling, the parameters that are not deterministic, uncertain, are represented with multiple scenarios instead of one. This is the main idea of stochastic modelling. The first step to make these scenarios is to know how to build a scenario tree for them. A scenario tree starts by making the scheduling decisions for the DA market. There is no step before the scheduling of the DA market and thus, it is the first decision in the decision tree. Since the day-ahead market prices are uncertain, a set of possible scenarios for the DA market price will be studied. Since there is a correlation [95] between the Day-ahead and real-time market prices, once a decision will be taken in the DA market, it will lead to a scenario ω . Where ω refers to the possible combinations of Day-ahead and real-time market prices that could happen on the next day. Once a scenario ω happens, the price of the day-ahead market will be known for sure and the real-time market price will be known for the hour that is right before the opening of the RT market and right after the closer of the DA market. The planning for the RT market starts after a scenario ω happens. At this step, there are multiple possible scenarios γ . Where γ refers to all the possible scenarios of the prices of the RT market and the stochastic units' production. The γ scenarios are evaluated for each time step in the RT market until the RT market scheduling ends. A timeline for this process is shown on Figure 3-9 to visualize this process. A general example will be given as well in order to make the process clearer.

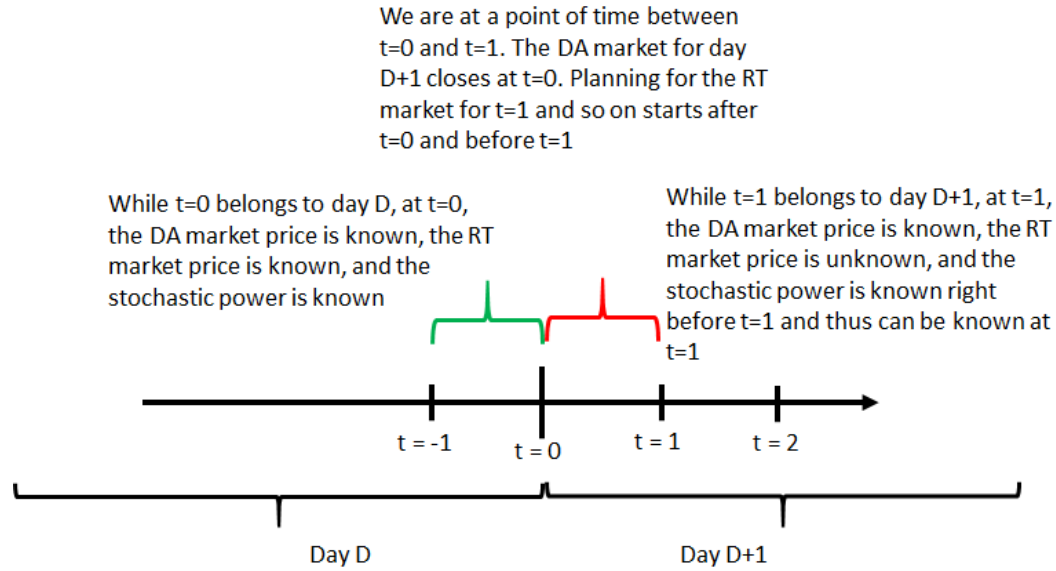


Figure 3-9 Stochastic Day-ahead and real-time markets timeline

Table 3-1 shows the prices of the DA market. There are two possible scenarios for that: **PDA1**, **PDA2**. There are also two possible scenarios for the production of the renewable energy sources: **pR1**, **pR2**. For the difference between the RT and DA prices, there are two scenarios PRT1 and PRT2. Under each scenario of those two, there are 2 more scenarios. The numbers highlighted in bold are known. Since there are two possible scenarios for the DA prices and two for the RT prices, that leads to four scenarios referred to as ω . Under each RT price, there are further 2 scenarios. Those two scenarios in combination with the two scenarios of the renewable energy production give four scenarios referred to as γ . Thus, there will be a total of 16 scenarios as shown on Table 3-2.

Table 3-1 Uncertain variables example

Time	Price DA		Price RT- Price DA				Renewable power production	
0	PDA1	PDA2	PRT1	PRT1	PRT2	PRT2	pR1	pR2
1	PDA11	PDA21	PRT11	PRT14	PRT21	PRT24	pR11	pR21
2	PDA12	PDA22	PRT12	PRT15	PRT22	PRT25	pR12	pR22

Time	Price DA		Price RT- Price DA				Renewable power production	
3	PDA13	PDA23	PRT13	PRT16	PRT23	PRT26	pR13	pR23
Probability	pPDA1	pPDA2	pPRT1	pPRT2	pPRT3	pPRT4	ppR1	ppR2

Table 3-2 Scenario tree example

Scenario	Price DA			Price RT- Price DA				Renewable units power production			Probability
	1	2	3	0	1	2	3	1	2	3	
w1y1	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T1}	PRT ₁₁	PRT ₁₂	PRT ₁₃	pR ₁₁	pR ₁₂	pR ₁₃	pPDA ₁ *pPRT ₁ *ppR ₁
w1y2	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T1}	PRT ₁₁	PRT ₁₂	PRT ₁₃	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above
w1y3	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T1}	PRT ₁₄	PRT ₁₅	PRT ₁₆	pR ₁₁	pR ₁₂	pR ₁₃	Calculated as above
w1y4	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T1}	PRT ₁₄	PRT ₁₅	PRT ₁₆	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above
w2y1	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T2}	PRT ₂₁	PRT ₂₂	PRT ₂₃	pR ₁₁	pR ₁₂	pR ₁₃	Calculated as above
w2y2	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T2}	PRT ₂₁	PRT ₂₂	PRT ₂₃	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above
w2y3	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T2}	PRT ₂₄	PRT ₂₅	PRT ₂₆	pR ₁₁	pR ₁₂	pR ₁₃	Calculated as above
w2y4	PDA ₁₁	PDA ₁₂	PDA ₁₃	PR _{T2}	PRT ₂₄	PRT ₂₅	PRT ₂₆	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above
w3y1	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T1}	PRT ₁₁	PRT ₁₂	PRT ₁₃	pR ₁₁	pR ₁₂	pR ₁₃	Calculated as above
w3y2	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T1}	PRT ₁₁	PRT ₁₂	PRT ₁₃	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above
w3y3	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T1}	PRT ₁₄	PRT ₁₅	PRT ₁₆	pR ₁₁	pR ₁₂	pR ₁₃	Calculated as above
w3y4	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T1}	PRT ₁₄	PRT ₁₅	PRT ₁₆	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above
w4y1	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T2}	PRT ₂₁	PRT ₂₂	PRT ₂₃	pR ₁₁	pR ₁₂	pR ₁₃	Calculated as above
w4y2	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T2}	PRT ₂₁	PRT ₂₂	PRT ₂₃	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above
w4y3	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T2}	PRT ₂₄	PRT ₂₅	PRT ₂₆	pR ₁₁	pR ₁₂	pR ₁₃	Calculated as above
w4y4	PDA ₂₁	PDA ₂₂	PDA ₂₃	PR _{T2}	PRT ₂₄	PRT ₂₅	PRT ₂₆	pR ₂₁	pR ₂₂	pR ₂₃	Calculated as above

The scenario table shows all the possible combinations/realizations under study. Once the DA scheduling is done, all the DA prices will be known, for day D+1, and the scenario ω will be selected/clear. The next stage will be the RT planning with the possible realizations

γ . Table 3-3 shows the status after the closure of the DA market and before the RT market planning starts. It can be seen that all the day-ahead market prices are known and thus their probability is 1. The RT market prices have two scenarios as they are still unknown except for time zero which is known. The production of the renewable energy resources is known for time zero and time 1. At this point, realizations γ are to be made. This is much easier than the case before as there are only four scenarios. This is because there are two possibilities for the RT prices, **PRT1**, **PRT2**, and two possibilities for the renewable energy production, **pR1**, **pR2**. These possible realizations are summarized in Table 3-4.

Table 3-3 Uncertain variables RT market, first hour

Time	Price DA	Price RT- Price DA		Renewable units power production	
0	PDA1	PRT1	PRT2	pR1	pR2
1	PDA11	PRT11	PRT21	pR11	pR21
2	PDA12	PRT12	PRT22	pR12	pR22
3	PDA13	PRT13	PRT23	pR13	pR23
Probability	1	pPRT1	pPRT2	ppR1	ppR2

Table 3-4 Possible realizations 'y', first hour

Scenario	Price RT- Price DA			Renewable units power production		Probability
	1	2	3	2	3	
y1	PRT11	PRT12	PRT13	pR12	pR13	pPRT1*ppR1
y2	PRT11	PRT12	PRT13	pR21	pR23	Calculated as above

Scenario	Price RT- Price DA			Renewable units power production		Probability
	1	2	3	2	3	
y3	PRT21	PRT22	PRT23	pR12	pR13	Calculated as above
y4	PRT21	PRT22	PRT23	pR21	pR23	Calculated as above

The last two steps are the planning for the second hour, out of a 3-hours planning horizon, and the third hour. The same methodology applied to the first hour can be applied to the second. Note that at this point, the renewable energy production for the second hour is known and the RT price for the first hour is known too. Therefore, the table will be as below.

Table 3-5 Uncertain variables RT market, second hour

Time	Price DA	Price RT- Price DA		Renewable units power production	
0	PDA1	PRT1	PRT2	pR1	pR2
1	PDA11	PRT11	PRT21	pR11	pR21
2	PDA12	PRT12	PRT22	pR12	pR22
3	PDA13	PRT13	PRT23	pR13	pR23
Probability	1	pPRT1	pPRT2	ppR1	ppR2

Table 3-6 Possible realizations ‘y’, second hour

Scenario	Price RT- Price DA		p Renewable	Probability
	2	3	3	
y1	PRT12	PRT13	pR13	pPRT1*ppR1

Scenario	Price RT- Price DA		p Renewable	Probability
	2	3	3	
y2	PRT12	PRT13	pR23	Calculated as above
y3	PRT22	PRT23	pR13	Calculated as above
y4	PRT22	PRT23	pR23	Calculated as above

The next two tables describe the last hour of the planning horizon for the RT market.

Table 3-7 Uncertain variables RT market, third hour

Time	Price DA	Price RT- Price DA		Renewable units power production
0	PDA1	PRT1	PRT2	pR1
1	PDA11	PRT11	PRT21	pR11
2	PDA12	PRT12	PRT22	pR12
3	PDA13	PRT13	PRT23	pR13
Probability	1	pPRT1	pPRT2	1

Table 3-8 Possible realizations ‘y’, third hour

Scenario	Price RT- Price DA	Probability
	3	
y1	PRT13	pPRT1
y2	PRT23	pPRT2

By this, the idea of building the decision tree and scenario realizations is fully clarified.

However, this is the first step towards making the stochastic optimization model for the

Day-ahead and real-time markets. The models explained will be incorporated with the technical models made for the RT and DA markets.

3.8.1 DA Market Stochastic Scheduling

The equations below are not different from the equations used to represent the deterministic model for the day-ahead market. The actual difference lies in the fact that the probability of each scenario is considered and of course, that multiple scenarios are considered. Therefore, the objective function will be expanded to cover all possible scenarios and each scenario will be multiplied by its probability. The second main difference is that the constraints will be in terms of ω and γ . This is to allow for the feasibility region to expand and cover all the possible scenarios.

$$\begin{aligned}
max_{\Phi^{DA,S}} \sum_{\omega} \sum_{\gamma} \pi_{\omega\gamma} \sum_{t \in \Omega^T} & [\lambda_{t\omega}^{DA} p_{t\omega}^{DA} \Delta t + \lambda_{t\omega\gamma}^{RT} p_{t\omega}^{RT} \Delta t \\
& + \sum_{d \in \Omega^D} U_{dt}^D p_{dt\omega\gamma}^D \Delta t \\
& + \sum_{c \in \Omega^C} (C_c^{C,V} p_{ct\omega\gamma}^C \Delta t + \bar{c}_{ct\omega\gamma}^C + \underline{c}_{ct\omega\gamma}^C)],
\end{aligned} \tag{3-75}$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\omega\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\omega\gamma}^L \\
& + \sum_{\ell | r(\ell)=n} p_{\ell t\omega\gamma}^L = p_{nt\omega\gamma}^M + \sum_{d \in \Omega_n^D} p_{dt\omega\gamma}^D, \forall n \in \Omega^M, \forall t \\
& \in \Omega^T, \forall \omega, \forall \gamma,
\end{aligned} \tag{3-76}$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\omega\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\omega\gamma}^L \\
& + \sum_{\ell | r(\ell)=n} p_{\ell t\omega\gamma}^L \& = \sum_{d \in \Omega_n^D} p_{dt\omega\gamma}^D, \forall n \in \Omega^N \setminus n \\
& \in \Omega^M, \forall t \in \Omega^T, \forall \omega, \forall \gamma,
\end{aligned} \tag{3-77}$$

$$p_{t\omega}^{DA} + p_{t\omega}^{RT} = \sum_{n \in \Omega^M} p_{nt\omega\gamma}^M, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \tag{3-78}$$

$$p_{\ell t\omega\gamma}^L = B_\ell(\delta_{s(\ell)t\omega\gamma} - \delta_{r(\ell)t\omega\gamma}), \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \tag{3-79}$$

$$-\bar{P}_\ell^L \leq p_{\ell t\omega\gamma}^L \leq \bar{P}_\ell^L \quad \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega, \forall \gamma \tag{3-80}$$

$$\delta_{nt\omega\gamma} = 0, n: \text{ref.}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \tag{3-81}$$

$$-\pi \leq \delta_{nt\omega\gamma} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \tag{3-82}$$

$$\underline{P}^V \leq p_{t\omega}^{\text{DA}} \leq \bar{P}^V, \forall t \in \Omega^T \quad (3-83)$$

$$\underline{P}^V \leq p_{t\omega}^{\text{DA}} + p_{t\omega}^{\text{RT}} \leq \bar{P}^V, \forall t \in \Omega^T, \forall \omega \quad (3-84)$$

$$-\bar{P}_n^{\text{M}} \leq p_{nt\omega\gamma}^{\text{M}} \leq \bar{P}_n^{\text{M}}, \forall n \in \Omega^{\text{M}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-85)$$

$$\sum_{t \in \Omega^T} p_{dt\omega\gamma}^{\text{D}} \Delta t \geq \underline{E}_d^{\text{D}}, \forall d \in \Omega^{\text{D}}, \forall \omega, \forall \gamma, \quad (3-86)$$

$$\underline{P}_{dt}^{\text{D}} \leq p_{dt\omega\gamma}^{\text{D}} \leq \bar{P}_{dt}^{\text{D}}, \forall d \in \Omega^{\text{D}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-87)$$

$$-R_d^{\text{D,D}} \Delta t \leq p_{dt\omega\gamma}^{\text{D}} - p_{d(t-1)\omega\gamma}^{\text{D}} \leq R_d^{\text{D,U}} \Delta t, \forall d \in \Omega^{\text{D}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-88)$$

$$\underline{P}_c^{\text{C}} u_{ct\omega\gamma}^{\text{C}} \leq p_{ct\omega\gamma}^{\text{C}} \leq \bar{P}_c^{\text{C}} u_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-89)$$

$$-R_c^{\text{C,D}} \Delta t \leq p_{ct\omega\gamma}^{\text{C}} - p_{c(t-1)\omega\gamma}^{\text{C}} \leq R_c^{\text{C,U}} \Delta t, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-90)$$

$$\bar{C}_c^{\text{C}} (u_{ct\omega\gamma}^{\text{C}} - u_{c(t-1)\omega\gamma}^{\text{C}}) \leq \bar{c}_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-91)$$

$$0 \leq \bar{c}_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-92)$$

$$\underline{C}_c^{\text{C}} (u_{c(t-1)\omega\gamma}^{\text{C}} - u_{ct\omega\gamma}^{\text{C}}) \leq \underline{c}_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-93)$$

$$0 \leq \underline{c}_{ct\omega\gamma}^c \forall c \in \Omega^c, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-94)$$

$$e_{st\omega\gamma}^S = e_{s(t-1)\omega\gamma}^S + \eta_s^{S,C} p_{st\omega\gamma}^{S,C} \Delta t - \frac{p_{st\omega\gamma}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-95)$$

$$\underline{E}_{st}^S \leq e_{st\omega\gamma}^S \leq \bar{E}_{st}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-96)$$

$$0 \leq p_{st\omega\gamma}^{S,C} \leq \bar{p}_s^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-97)$$

$$0 \leq p_{st\omega\gamma}^{S,D} \leq \bar{p}_s^{S,D}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-98)$$

$$p_{st\omega\gamma}^S = p_{st\omega\gamma}^{S,D} - p_{st\omega\gamma}^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega, \forall \gamma \quad (3-99)$$

$$0 \leq p_{rt\omega\gamma}^R \leq p_{rt\omega\gamma}^{R,A}, \forall r \in \Omega^R, \forall t \in \Omega^T, \forall \omega, \forall \gamma \quad (3-100)$$

$$p_{t\omega}^{DA} \leq p_{t\omega'}^{DA}, \text{ if } \lambda_{t\omega}^{DA} \leq \lambda_{t\omega'}^{DA}, \forall t \in \Omega^T, \forall \omega, \forall \omega' \quad (3-101)$$

$$p_{t\omega}^{DA} = p_{t\omega'}^{DA}, \text{ if } \lambda_{t\omega}^{DA} = \lambda_{t\omega'}^{DA}, \forall t \in \Omega^T, \forall \omega, \forall \omega' \quad (3-102)$$

Another difference compared to the deterministic model is the addition of the last two equations. The addition of the last two equations also implies the need for adding the subscript ω to the DA market power. Equation (3-101) is required for a non-decreasing behavior. This means that the offer/bid submitted to the market operator will be a combination of power and price and it will be in a non-decreasing form as required by the market operator. To make the idea clearer, consider the two cases of bidding and offering. When bidding, the power has a negative sign (purchasing) and it has a price pair, call it price1. Thus, the pair would be (-power1, price1). Consider another bid with higher price, price3. Since price3 is higher than price1, then -power3 shall be greater than -power1. This in fact means that the higher the price, the less is the purchased power which makes sense. This is happening due to the negative sign in the Boolean equation. When offering, the power has a positive sign (selling) and it has a price pair, call it price2. Consider another offer with higher price, price4. Since price4 is higher than price2, then power4 shall be greater than power2. This means that the higher the price, the more power is offered for selling to maximize the profit. On the other hand, equation (3-102) implies that if there are two scenarios with the same expected price, they should have the same power pair.

3.8.2 RT Market Stochastic Scheduling

The same concept applied to the DA deterministic and stochastic markets is applied to the RT deterministic and stochastic markets. This means that the equations will be the same with two main differences. The first one is that the objective function will be scenario dependent. The second difference is that the constraints will be in terms of the γ scenarios.

$$\begin{aligned}
& \max_{\Phi^{RT,S}} \sum_{\gamma \in \Pi^{RT}} \pi_{\gamma} \sum_{t \in \tau} \frac{|\Omega^T|}{|\Omega^T|} [\lambda_{t\gamma}^{RT} p_t^{RT} \Delta t + \sum_{d \in \Omega^D} U_{dt}^D p_{dt\gamma}^D \Delta t \\
& \quad - \sum_{c \in \Omega^C} (C_c^{C,V} p_{ct\gamma}^C \Delta t + \bar{c}_{ct\gamma}^C + \underline{c}_{ct\gamma}^C)]
\end{aligned} \tag{3-103}$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\gamma}^L \\
& \quad = p_{nt\gamma}^M + \sum_{d \in \Omega_n^D} p_{dt\gamma}^D, \forall n \in \Omega^M, \forall t \geq \tau, \forall \gamma,
\end{aligned} \tag{3-104}$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\gamma}^L \& \\
& \quad = \sum_{d \in \Omega_n^D} p_{dt\gamma}^D, \forall n \in \Omega^N \setminus n \in \Omega^M, \forall t \geq \tau, \forall \gamma,
\end{aligned} \tag{3-105}$$

$$\hat{p}_t^{DA} + p_t^{RT} = \sum_{n \in \Omega^M} p_{nt\gamma}^M, \forall t \geq \tau, \forall \gamma, \tag{3-106}$$

$$p_{\ell t\gamma}^L = B_{\ell}(\delta_{s(\ell)t\gamma} - \delta_{r(\ell)t\gamma}), \forall \ell \in \Omega^L, \forall t \geq \tau, \forall \gamma, \tag{3-107}$$

$$-\bar{P}_{\ell}^L \leq p_{\ell t\gamma}^L \leq \bar{P}_{\ell}^L \quad \forall \ell \in \Omega^L, \forall t \geq \tau, \forall \gamma \tag{3-108}$$

$$\delta_{nt\gamma} = 0, n: \text{ref.}, \forall t \geq \tau, \forall \gamma, \quad (3-109)$$

$$-\pi \leq \delta_{nt\gamma} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \geq \tau, \forall \gamma, \quad (3-110)$$

$$\underline{P}^V \leq \tilde{p}_t^{\text{DA}} + p_t^{\text{RT}} \leq \bar{P}^V, \forall t \geq \tau \quad (3-111)$$

$$-\bar{P}_n^{\text{M}} \leq p_{nt\gamma}^{\text{M}} \leq \bar{P}_n^{\text{M}}, \forall n \in \Omega^{\text{M}}, \forall t \geq \tau, \forall \gamma, \quad (3-112)$$

$$\sum_{t=1}^{\tau-1} \tilde{p}_{dt}^{\text{D}} \Delta t + \sum_{t=\tau}^{|\Omega^{\text{T}}|} p_{dt\gamma}^{\text{D}} \Delta t \geq \underline{E}_d^{\text{D}}, \forall d \in \Omega^{\text{D}}, \forall \gamma, \quad (3-113)$$

$$\underline{P}_{dt}^{\text{D}} \leq p_{dt\gamma}^{\text{D}} \leq \bar{P}_{dt}^{\text{D}}, \forall d \in \Omega^{\text{D}}, \forall t \geq \tau, \forall \gamma, \quad (3-114)$$

$$-R_d^{\text{D,D}} \Delta t \leq p_{dt\gamma}^{\text{D}} - p_{d(t-1)\gamma}^{\text{D}} \leq R_d^{\text{D,U}} \Delta t, \forall d \in \Omega^{\text{D}}, \forall t \geq \tau, \forall \gamma, \quad (3-115)$$

$$\underline{P}_c^{\text{C}} u_{ct\gamma}^{\text{C}} \leq p_{ct\gamma}^{\text{C}} \leq \bar{P}_c^{\text{C}} u_{ct\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \geq \tau, \forall \gamma, \quad (3-116)$$

$$-R_c^{\text{C,D}} \Delta t \leq p_{ct\gamma}^{\text{C}} - p_{c(t-1)\gamma}^{\text{C}} \leq R_c^{\text{C,U}} \Delta t, \forall c \in \Omega^{\text{C}}, \forall t \geq \tau, \forall \gamma, \quad (3-117)$$

$$\bar{C}_c^{\text{C}} (u_{ct\gamma}^{\text{C}} - u_{c(t-1)\gamma}^{\text{C}}) \leq \bar{c}_{ct\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \geq \tau, \forall \gamma, \quad (3-118)$$

$$0 \leq \bar{c}_{ct\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \geq \tau, \forall \gamma, \quad (3-119)$$

$$\underline{c}_c^C(u_{c(t-1)\gamma}^C - u_{ct\gamma}^C) \leq \underline{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-120)$$

$$0 \leq \underline{c}_{ct\gamma}^C \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-121)$$

$$e_{st\gamma}^S = e_{s(t-1)\gamma}^S + \eta_s^{S,C} p_{st\gamma}^{S,C} \Delta t - \frac{p_{st\gamma}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-122)$$

$$\underline{E}_{st}^S \leq e_{st\gamma}^S \leq \bar{E}_{st}^S, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-123)$$

$$0 \leq p_{st\gamma}^{S,C} \leq \bar{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-124)$$

$$0 \leq p_{st\gamma}^{S,D} \leq \bar{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-125)$$

$$p_{st\gamma}^S = p_{st\gamma}^{S,D} - p_{st\gamma}^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma \quad (3-126)$$

$$0 \leq p_{rt\gamma}^R \leq \tilde{P}_{rt\gamma}^{R,A}, \forall r \in \Omega^R, \forall t = \tau, \forall \gamma \quad (3-127)$$

$$0 \leq p_{rt\gamma}^R \leq P_{rt\gamma}^{R,A}, \forall r \in \Omega^R, \forall t > \tau, \forall \gamma \quad (3-128)$$

$$p_{t\gamma}^{\text{RT}} \leq p_{t\gamma'}^{\text{RT}}, \quad \text{if } \lambda_{t\gamma}^{\text{RT}} \leq \lambda_{t\gamma'}^{\text{RT}}, \forall t \in \Omega^{\text{T}}, \forall \gamma, \forall \gamma' \quad (3-129)$$

$$p_{t\gamma}^{\text{RT}} = p_{t\gamma'}^{\text{RT}}, \quad \text{if } \lambda_{t\gamma}^{\text{RT}} = \lambda_{t\gamma'}^{\text{RT}}, \forall t \in \Omega^{\text{T}}, \forall \gamma, \forall \gamma' \quad (3-130)$$

The last two equations are added for a non-decreasing power-price pair submittal and for ensuring that the same price level will have the same power quantity, respectively. It can be seen that if there are 16 scenarios for example, each equation will be replaced by 16 equations. This heavily affects the computational time. Robust optimization plays a crucial role in reducing this computational time.

3.9 Scheduling Considering Risk

The robust optimization adds the risk factor into the calculation. In both the deterministic and stochastic techniques that were discussed earlier, the risk was not included into the models. In the robust optimization models, risk will be included in different ways depending on the model. Four models will be discussed in this section. The first one is the stochastic model which represents the uncertain parameters through scenarios. The second one is the static robust optimization which represents the uncertain parameters through confidence bounds. Combining the previous two models results in the third one which is the hybrid stochastic robust model. In this case, both scenarios and confidence bounds will be used. The last model is the adaptive robust optimization model. It is called adaptive because it has the ability to adapt, take corrective actions, after a realization is reached.

3.9.1 Stochastic Programming Considering Risk

Risk is incorporated in this model through the conditional value at risk (CVaR) metric. The model is very similar to the aforementioned ones. It is represented by the equations below.

$$\max_{\Phi^{\text{DA},S}} \sum_{\omega \in \Pi^{\text{DA}}} \pi_{\omega} \zeta_{\omega} + \beta \left[\rho - \frac{1}{1-\alpha} \sum_{\omega \in \Pi^{\text{DA}}} \pi_{\omega} \mu_{\omega} \right] \quad (3-131)$$

$$\begin{aligned} \zeta_{\omega} = \sum_{t \in \Omega^{\text{T}}} & \left[\lambda_{t\omega}^{\text{DA}} p_t^{\text{DA}} \Delta t + \lambda_{t\omega}^{\text{RT}} p_{t\omega}^{\text{RT}} \Delta t \right. \\ & \left. + \sum_{d \in \Omega^{\text{D}}} U_{dt}^{\text{D}} p_{dt\omega}^{\text{D}} \Delta t - \sum_{c \in \Omega^{\text{C}}} (C_c^{\text{C},\text{F}} u_{ct}^{\text{C}} + C_c^{\text{C},\text{V}} p_{ct\omega}^{\text{C}} \Delta t) \right], \forall \omega \\ & \in \Pi^{\text{DA}}, \end{aligned} \quad (3-132)$$

$$-\zeta_{\omega} + \rho - \mu_{\omega} \leq 0, \forall \omega \in \Pi^{\text{DA}}, \quad (3-133)$$

$$0 \leq \mu_{\omega}, \forall \omega \in \Pi^{\text{DA}} \quad (3-134)$$

$$\begin{aligned} \sum_{c \in \Omega_n^{\text{C}}} p_{ct\omega}^{\text{C}} + \sum_{r \in \Omega_n^{\text{R}}} p_{rt\omega}^{\text{R}} + \sum_{s \in \Omega_n^{\text{D}}} (p_{st\omega}^{\text{SD}} - p_{st\omega}^{\text{S,C}}) - \sum_{\ell | S(\ell)=n} p_{\ell t\omega}^{\text{L}} \\ + \sum_{\ell | r(\ell)=n} p_{\ell t\omega}^{\text{L}} = p_{nt\omega}^{\text{M}} + \sum_{d \in \Omega_n^{\text{D}}} p_{dt\omega}^{\text{D}}, \forall n \in \Omega^{\text{M}}, \forall t \\ \in \Omega^{\text{T}}, \forall \omega \in \Pi^{\text{DA}} \end{aligned} \quad (3-135)$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\omega}^C + \sum_{r \in \Omega_n^R} p_{rt\omega}^R + \sum_{s \in \Omega_n^S} (p_{st\omega}^{S,D} - p_{st\omega}^{S,C}) - \sum_{\ell | s(\ell)=n} p_{\ell t\omega}^L \\
& + \sum_{\ell | r(\ell)=n} p_{\ell t\omega}^L = \sum_{d \in \Omega_n^D} p_{dt\omega}^D, \forall n \in \Omega^N \setminus n \in \Omega^M, \forall t \\
& \in \Omega^T, \forall \omega \in \Pi^{DA}
\end{aligned} \tag{3-136}$$

$$p_t^{DA} + p_{t\omega}^{RT} = \sum_{n \in \Omega^M} p_{nt\omega}^M, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \tag{3-137}$$

$$p_{\ell t\omega}^L = B_\ell (\delta_{s(\ell)t\omega} - \delta_{r(\ell)t\omega}), \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \tag{3-138}$$

$$-\bar{P}_\ell^L \leq p_{\ell t\omega}^L \leq \bar{P}_\ell^L, \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \tag{3-139}$$

$$\delta_{nt\omega} = 0, n: \text{ref.}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \tag{3-140}$$

$$-\pi \leq \delta_{nt\omega} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \tag{3-141}$$

$$\underline{P}^V \leq p_t^{DA} \leq \bar{P}^V, \forall t \in \Omega^T \tag{3-142}$$

$$\underline{P}^V \leq p_t^{DA} + p_{t\omega}^{RT} \leq \bar{P}^V, \forall t \in \Omega^T, \forall \omega \tag{3-143}$$

$$-\bar{P}_n^M \leq p_{nt\omega}^M \leq \bar{P}_n^M, \forall n \in \Omega^M, \forall t \in \Omega^D, \forall \omega \in \Pi^{DA} \tag{3-144}$$

$$\sum_{t \in \Omega^T} p_{dt\omega}^D \Delta t \geq \underline{E}_d^D, \forall d \in \Omega^D, \forall \omega \in \Pi^{DA} \quad (3-145)$$

$$\underline{p}_{dt}^D \leq p_{dt\omega}^D \leq \bar{p}_{dt}^D, \forall d \in \Omega^D, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \quad (3-146)$$

$$\begin{aligned} -R_d^{D,D} \Delta t \leq p_{dt\omega}^D - p_{d(t-1)\omega}^D \leq R_d^{D,U} \Delta t, \forall d \in \Omega^D, \forall t \in \Omega^T, \forall \omega \\ \in \Pi^{DA} \end{aligned} \quad (3-147)$$

$$\underline{p}_c^C u_{ct}^C \leq p_{ct\omega}^C \leq \bar{p}_c^C u_{ct}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \quad (3-148)$$

$$-R_c^{C,D} \Delta t \leq p_{ct\omega}^C - p_{c(t-1)\omega}^C \leq R_c^{C,U} \Delta t, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \quad (3-149)$$

$$\begin{aligned} e_{st\omega}^S = e_{s(t-1)\omega}^S + \eta_s^{S,C} p_{st\omega}^{S,C} \Delta t - \frac{p_{st\omega}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \\ \in \Pi^{DA} \end{aligned} \quad (3-150)$$

$$\underline{E}_{st}^S \leq e_{st\omega}^S \leq \bar{E}_{st}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \quad (3-151)$$

$$0 \leq p_{st\omega}^{S,C} \leq \bar{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \quad (3-152)$$

$$0 \leq p_{st\omega}^{S,D} \leq \bar{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \quad (3-153)$$

$$0 \leq p_{rt\omega}^R \leq p_{rt\omega}^{R,A}, \forall r \in \Omega^R, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA} \quad (3-154)$$

It is clear that the equations are almost identical to the stochastic model without risk consideration. The key difference actually lies within the objective function which has two terms in which the first term is related to maximizing the profit as in the previous models. The second is in terms of the CVaR. Note that the weighing factor β controls the effect of the CVaR. If it is equal to zero, the model will be the same as the risk-free model discussed earlier. If it is greater than zero, risk will be incorporated in the model which would in return reduce the expected profit. Equations (3-133) and (3-134) are added in order to incorporate the CVaR as a set of linear equations into the model. Further details on the derivation of this process of CVaR addition can be found in [96].

3.9.2 Robust Optimization

In this section, robust optimization is briefly introduced and a table of comparison is shown below in order to make it easier understanding the reason behind moving from one model to another.

Table 3-9 Comparison between the optimization models

Model	Advantages	Disadvantages
Deterministic	Easier, and requires less computation time	Does not cover all possibilities

Model	Advantages	Disadvantages
Stochastic with no Risk	Better results compared to the deterministic model	Requires a big number of scenarios, more computational time, and knowledge about the probability distribution of the uncertain parameters. It also does not consider risk. Limited feasible operation and requires a big number of scenarios.
Stochastic with Risk	Better results compared to the deterministic model. It also considers the risk factor.	Requires a big number of scenarios, more computational time, and knowledge about the probability distribution of the uncertain parameters. Limited feasible operation and requires a big number of scenarios.
Static Robust	Easier to generate confidence bounds compared to scenarios. Less computational time compared to the stochastic model. More reliable compared to the stochastic	Can be/ is very pessimistic/ conservative.

Model	Advantages	Disadvantages
	model as it considers the worst-case scenario.	
Hybrid Robust	A balance between the stochastic with risk and the static robust methods. It considers scenarios for the objective function and confidence bounds for the constraints	Does not consider the ability of taking corrective actions. Very conservative
Adaptive Robust Optimization	It gives the VPP the ability to take corrective actions assuming the worst-case scenario realization has happened	Mathematically complex and requires solving three levels optimization problem. Very conservative

Based on the information in the table above, it is important to note that confidence bounds will be considered instead of or along with scenarios in robust models. As discussed earlier, and due to the correlation between the Day-ahead and real-time prices, the RT price can be written in terms of the DA price with the aid of an extra term called the residual. This is based on the analysis in [95] which has found out that the RT and DA market prices are highly correlated. On the other hand, it was found that the residual prices and the DA

market prices are not highly correlated and thus, each of them can now be used as an independent random variable.

$$\lambda_t^{\text{RT}} = \lambda_t^{\text{DA}} + r_t^{\text{RT}}, \forall t \in \Omega^{\text{T}} \quad (3-155)$$

Based on the equation above, the confidence bounds can be defined as:

$$\lambda_t^{\text{DA}} \in [\tilde{\lambda}_t^{\text{DA}} - \hat{\lambda}_t^{\text{DA}}, \tilde{\lambda}_t^{\text{DA}} + \hat{\lambda}_t^{\text{DA}}], \forall t \in \Omega^{\text{T}} \quad (3-156)$$

$$r_t^{\text{RT}} \in [\tilde{r}_t^{\text{RT}} - \hat{r}_t^{\text{RT}}, \tilde{r}_t^{\text{RT}} + \hat{r}_t^{\text{RT}}], \forall t \in \Omega^{\text{T}} \quad (3-157)$$

$$p_{rt}^{\text{R,A}} \in [\tilde{p}_{rt}^{\text{R,A}} - \hat{p}_{rt}^{\text{R,A}}, \tilde{p}_{rt}^{\text{R,A}} + \hat{p}_{rt}^{\text{R,A}}], \forall t \in \Omega^{\text{T}}, \forall r \in \Omega^{\text{R}} \quad (3-158)$$

The terms with the $\sim$ sign refer to the nominal or average value of the parameter while the terms with the $\wedge$ sign refer to the deviation from the nominal value. The deviation terms are all positive. We can now define two sets where the first one is the set of prices J^{DA} . Since for each time period there are two prices, the DA and the RT, the cardinality of this set would be $2|\Omega^{\text{T}}|$. The other set contains the other uncertain parameter $p_{rt}^{\text{R,A}}$ which will be called J_{rt}^{R} . For each time period, for each renewable energy resource, this set will contain only one element and thus have a cardinality of one. Therefore, the confidence bounds parameters Γ^{DA} and Γ_{rt}^{R} can be defined. They can take the values of $[0 \text{ to } 2|\Omega^{\text{T}}|]$ and $[0 \text{ to } 1]$ respectively. Where zero means ignoring risk and the right-hand side limit means taking the most conservative scenario.

3.10 Notes on The Models

The following models were discussed in detail in the previous sections: deterministic model, stochastic model with no risk, and stochastic model with risk. Also, the robust models presented are: static, hybrid stochastic, and adaptive. Each model has its advantages and disadvantages. It can be noted however that some models are more detailed than the others. Some require deep interaction with the mathematical background of linear programming and some do not. Some models require the use of linear programming techniques are duality, linearization of nonlinear equations, and the conversion of multiple stage LP into a single LP.

The deterministic model is the simplest. The stochastic model is balanced in terms of complexity, accuracy, and computational time. However, the consideration of risk is important and thus, the stochastic model with risk is a better choice in this case. The robust optimization models though being more conservative, they can be computationally costly and mathematically involved. Also, extreme conservativeness is not necessarily the best option in assessing the market and the profitability. As a balance between complexity, conservativeness and accuracy, the stochastic model with risk will be considered. Also, robust optimization works when confidence bounds are available. When they are not, it becomes infeasible to use robust optimization. For stochastic programming, scenarios can be generated based on historical data. Historical data is usually available. Nevertheless, the RT model for this technique was not presented in the literature. Therefore, before advancing to the next sections, all the constraints will be combined from all the mentioned techniques to make a more comprehensive form of the stochastic model with risk for the

DA market. Additionally, the model for the RT market will be developed from the DA market model. As per [198], stochastic programming was found a much better choice in terms of tradeoff between cost and risk compared to robust programming even when setting the robust programming risk parameters to the less conservative values. In addition to the fact that robust optimization is more mathematically complex and more conservative. This makes stochastic programming with risk a balance between complexity, conservativeness, and accuracy. When the distribution function of the unknown parameters is unknown, robust optimization can be selected as an alternative to stochastic programming. Lastly, stochastic programming works directly on the objectives such as maximizing the profit or minimizing the cost while robust optimization works on maximizing the minimum profit or minimizing the maximum cost which makes robust optimization very conservative naturally even when the parameters of conservativeness are lowered.

3.11 Historical Data Modelling

Regardless to the model of choice, three main historical data inputs are required. The first is the renewable energy source input which will be considered as a wind turbine for example. The second is the historical prices of the day ahead market and the third one is the real time market prices. Those three inputs have one thing in common. They all require historical data modelling for the purpose of forecasting the studied time frame which is the next 24 hours in this study. There are several modelling techniques for historical data and one of the most popular methods is the autoregressive moving average (ARMA) model. The term ARMA is composed of the autoregressive segment (AR) and the moving average segment (MA). There are other forms of the ARIMA model. One of which is the ARIMA

model which has an integration term (I). Another one is the SARIMA where the (S) term stands for seasonal. One more variation is the SARIMAX model where the term (X) stands for an exogenous variable i.e., the model uses more than one independent variable of historical data. The selection of the order of each segment of the SARIMAX is based on the historical data type and properties.

3.11.1 ARIMA Model

The ARIMA model is going to be built in a step-by-step process starting with the AR part.

An AR model is represented as:

$$X_t = c + \sum_{i=1}^p \phi_i X_{t-i} + \varepsilon_t \quad (3-159)$$

Which can be expanded as:

$$X_t - \phi_1 X_{t-1} - \dots - \phi_p X_{t-p} = c + \varepsilon_t \quad (3-160)$$

By using a lag operator B^p which represents a difference of order p it becomes:

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) X_t = c + \varepsilon_t \quad (3-161)$$

Which is equivalent to:

$$\phi(B)X_t = c + \varepsilon_t \quad (3-162)$$

Where $\phi(B)$ is defined as:

$$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) \quad (3-163)$$

This means that a variable X in terms of time t can be represented in terms of some p points of the historical data of X in addition to a constant c and an error term ε_t . The error term here is generally represented by a gaussian distribution with zero mean and constant variance. If the error term is also represented by a lag function similar to $\phi(B)$, it is called a MA representation which will produce the ARMA model.

$$\phi(B)X_t = c + \theta(B)\varepsilon_t \quad (3-164)$$

Integration is when the function X_t is differenced. Integration is usually done in the order of 1 and sometime the order of 2. This can be represented by $(1-B)$ term multiplied by X_t which simply means $X_t - X_{t-1}$. Therefore, ARIMA model will be represented as:

$$\phi(B)(1 - B)X_t = c + \theta(B)\varepsilon_t \quad (3-165)$$

Seasonality means doing the difference at specific points where repetition happens seasonally. For example, if some data repeats with a similar fashion every 24 hours, it will

have a seasonality of 24 which can be treated as differencing in the order of 24. Thus, SARIMA could look like this:

$$\phi(B)(1 - B)(1 - B)^s X_t = c + \theta(B)\varepsilon_t \quad (3-166)$$

Where s is the differencing order. It can be 24 for daily, or 168 for weekly seasonality. The last part is the X part which can be added to SARIMA to produce the SARIMAX model as:

$$\phi(B)(1 - B)(1 - B)^s X_t = c + \beta Y_t + \theta(B)\varepsilon_t \quad (3-167)$$

Where Y is the other variable considered. For example, X and Y can be wind speed and wind power when forecasting the wind power of a wind generator. SARIMAX stands for Seasonal Auto Regressive Integrated Moving Average with exogenous factors.

3.11.2 ACF and PACF

An ARIMA model has three unknowns to be selected before doing the model fitting. Those three parameters are p, d, and q. Where p is the AR order, q is the MA order and d is the integration order. ARIMA (p, d, q) is how this model is represented. The selection process of those parameters is not a straight forward process as it requires experience in addition to the mathematical tools. First, by looking at the timeseries of the data, trend, volatility, seasonality and other characteristics can be noted. If there is volatility and/or a trend, it is

better to use a transformation technique before proceeding in order to eliminate this trend. Transformation techniques can be the natural logarithmic function, the cubic root, or others. The logarithmic function is one of the most popular for positive data. For negative data, modifications of the logarithmic functions exist such as adding a small constant to the time series which is not statistically favorable.

After this step, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) can be plotted for further analysis. The ACF is generally concerned with the order of q while the PACF is related to the order of p . If for example the ACF has a cut off after q lags and the PACF dies exponentially or sinusoidally, then it is a MA model with order q . If the opposite behavior happens between the ACF and the PACF, it is an AR model with order p . The analysis become more difficult if the ACF and/or the PACF does not die out or cut off. This can be a sign for the need of differencing which usually has an order of 1 or 2. If differencing is done and the ACF and PACF are still fluctuating without a specific pattern that leads to deciding the order of p and q , the model might be ARIMA/ARMA. This is where experience and other statistical tools are needed. If the data is for example hourly and there is a spike every 24 lags, this can a sign of a seasonality which needs to be addressed in the model to turn it into SARMA/SARIMA. One of the most popular tools for deciding the order of p and q after that are the extended ACF (EACF), Akaike's Information Criteria (AIC), and Bayesian Information Criteria (BIC). The working principle is the same for those techniques. A table is made where the header row has the order of q and the header column has the order of p ranked from one to any desired degree, say 5. For each cell ordered as (p, q) , a statistical value, say the BIC, is noted. Based on

these values, the order of p and q can be figured out. For example, for the case of BIC, the cell at which the BIC is minimum is selected as the order of (p, q) . Table 3-10 shows an example where p and q are selected to be equal to three. Further details on ACF and PACF can be found in [155] and [156] while EACF is explained with numerical examples in [157].

Table 3-10 BIC example

	$q=1$	$q=2$	$q=3$	$q=4$	$q=5$
$p=1$	862.9	863.4	866.1	869.2	874.5
$p=2$	863.8	864.3	871.5	865.2	865.9
$p=3$	866.7	868.4	847.6	868.9	873.2
$p=4$	872.2	861.2	866.5	872.8	872.1
$p=5$	854.7	863.3	868.2	877.2	864.7

There are other techniques to model such historical data such as neural networks and transfer function. Transfer function has shown good capabilities while neural networks are less powerful compared to ARIMA and transfer function when it comes to historical data modelling and fitting such as the wind power and market prices [158]. The market prices do not have one specific model to represent them as the model can vary based on the market behavior [159]. Generally, a univariate model is used where only one historical variable is used but in cases where the data is difficult to model, such as the wind power, multivariate models can be useful [160]. For wind power modelling specifically, nonlinear fitting can be utilized [161]. If there are multiple wind turbines in the studied grid, the model could be slightly modified to account for modelling multiple wind turbines in multiple locations [162]. Finally, when modelling uncertain data, multiple scenarios are generated, and this

number of scenarios might be big which adds a burden onto the calculation time and for this, scenario reduction models can be utilized [163].

3.11.3 Scenario Generation

After developing a model for the historical data, say ARIMA, scenarios can be generated. Scenarios are usually generated in large numbers which adds computational burden, and this can be handled through the use of scenario reduction techniques. The general idea of reducing the number of scenarios is to remove the scenarios with the lowest probability and group the scenarios that are close to each other [164]. The process of scenario generation and reduction can be summarized in a number of steps as follows:

1. The historical data has to be prepared and the regression model, say ARIMA has to be estimated.
2. If N scenarios are to be made, start with scenario $w=1$.
3. If the time steps are T , start with time $t=1$.
4. Based on the error of the ARIMA model, which is a normally distributed error with zero mean and a standard deviation σ , generate a random number R .
5. Evaluate/simulate the ARIMA model with the obtained error and other parameters.
6. If N is reached, move to the next step, otherwise, set $w=w+1$ and go to step 4.
7. Assign each scenario a probability. This has to be updated every time a new scenario is added. If N scenarios are there, and they have equal probability, each will have probability $1/N$.

8. Use a scenario reduction technique in order to reduce the number of scenarios if required.
9. If T is reached, move to the next step, otherwise, set $t=t+1$ and go to step 2.
10. End

Figure 3-10 shows the flowchart of the steps above.

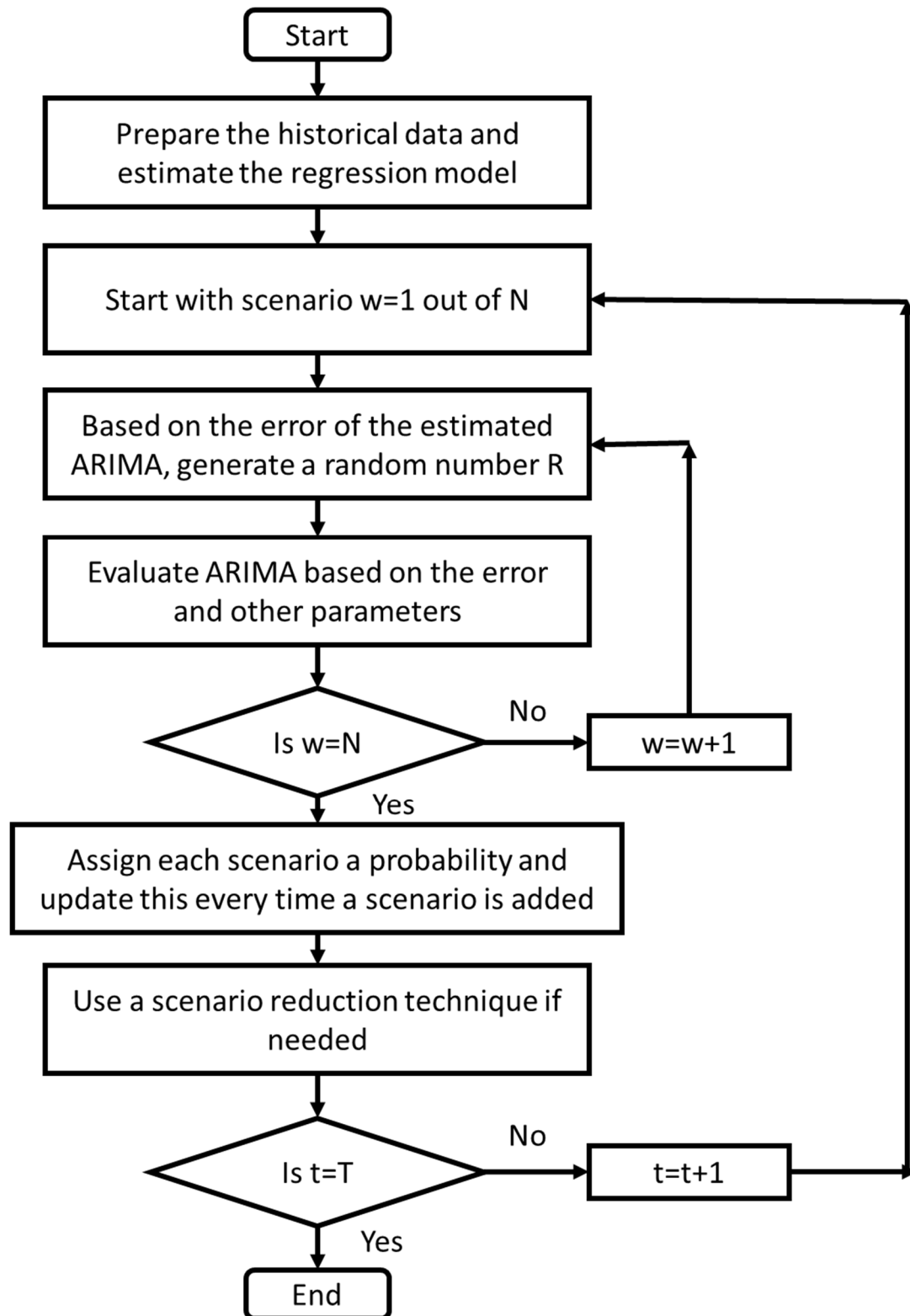


Figure 3-10 Scenario generation and reduction flowchart

3.12 Wind Turbine Mathematical Model

To get the power output of a wind turbine using the mathematical calculations, the wind speed has to be obtained and forecasted as explained in the previous sections. This wind speed can then be converted to wind power. The relationship curve between the wind speed and wind power looks like Figure 3-11. It can be seen that the figure has two flat areas and one nonlinear segment. The modelling of the relationship between the wind speed and wind power differs due to the representation of this nonlinear region. Different references in the literature use different ways to represent this region [165] to [167].

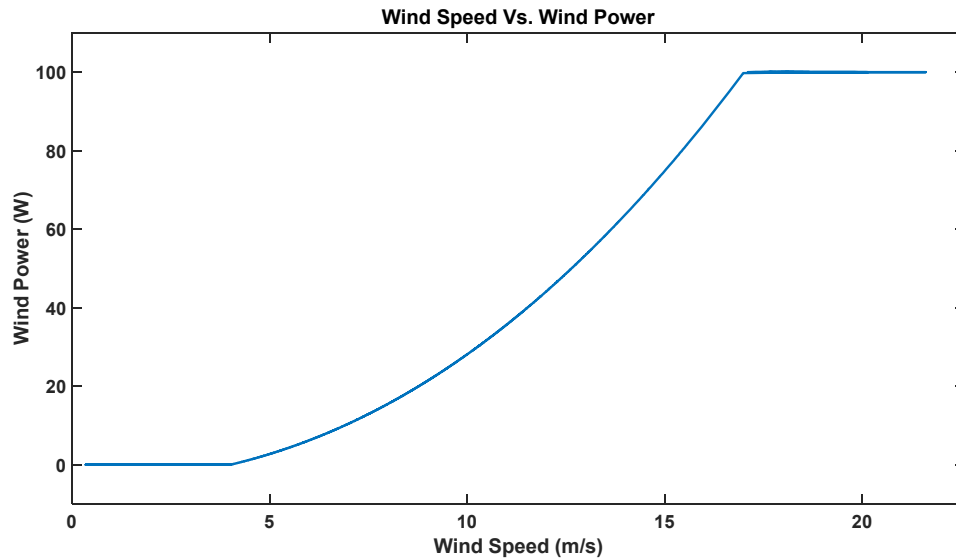


Figure 3-11 Wind power and speed relationship

There are three main parameters that need to be defined on the curve. The first one is the cut-in speed. This is the wind speed before which the wind turbine does not produce any power and after which the wind turbine starts producing power. The rated speed after which the wind turbine produces power equals its rated power. The cut-out speed which is the

speed at which the turbine stops producing power for protection purposes. The nonlinear region is the region between the cut-in and rated speeds. This behavior is defined using a piecewise function as below:

$$P^w = \left\{ \begin{array}{ll} 0 & , v < v_{ci} \\ C1 + C2 v^b & , v_{ci} < v < v_r \\ P_r^w & , v_r < v < v_{co} \\ 0 & , v_{co} < v \end{array} \right\} \quad (3-168)$$

Where C1 and C2 are defined as:

$$C1 = P_r^w \frac{v_{ci}^b}{v_{ci}^b - v_r^b} \quad (3-169)$$

$$C2 = \frac{P_r^w}{v_r^b - v_{ci}^b} \quad (3-170)$$

Where P_r^w is the rated wind power of the turbine, v_r is the rated wind speed of the turbine, v_{ci} and v_{co} are the cut in and cut out speeds respectively. The term b is the shape factor of the Weibull distribution which is the probability distribution function that suits the wind speed data.

3.13 Generator Variable Cost in LP

In general, for simplicity, in literature, the conventional generator's variable cost is taken as a fixed number. This is especially the case when the model is made through linear

programming. This is because the variable cost is not by itself a linear equation. It is a piecewise function. This piecewise function is by itself an approximation to a nonlinear function. In this work, the piecewise function will be converted to a linear model in order to be incorporated into the MILP. This will be done through the special-order set (SOS) constraint of type 2. To explain this, the following example will be explained:

$$Z = \begin{cases} a_1x + b_1 & , l_1 < x < l_2 \\ a_2x + b_2 & , l_2 < x < l_3 \\ a_3x + b_3 & , l_3 < x < l_4 \end{cases} \quad (3-171)$$

The first constraint is $l_1 < x < l_4$. Then, the conversion model will start by introducing four non-negative variables x_1 to x_4 .

$$x = l_1x_1 + l_2x_2 + l_3x_3 + l_4x_4 \quad (3-172)$$

Where each new variable is multiplied by one of the limits of the piecewise function. This is subject to:

$$1 = x_1 + x_2 + x_3 + x_4 \quad (3-173)$$

We can now define Z by substituting each limit into its respective equation and adding them up.

$$\begin{aligned}
Z = & (a_{1l1} + b_1) x_1 + (a_{1l2} + b_1) x_2 + (a_{3l3} + b_3) x_3 \\
& + (a_{4l4} + b_4) x_4
\end{aligned} \tag{3-174}$$

By this, the model is ready except for one issue. The system will go out of the feasible region for some values of x_i . This is where the role of SOS type 2 handles this issue. There must be restriction on x_i such that only two x_i can be nonzero at a time and they must be two consecutive x_i . For example, x_1 and x_4 cannot both be nonzero at the same time because they are not adjacent [168]. This requires the introduction of binary variables Y_i such that:

$$x_i \leq y_i \text{ for all } i$$

$$\sum y_i \leq 2$$

$$y_1 + y_3 \leq 1 \tag{3-175}$$

$$y_1 + y_4 \leq 1$$

$$y_2 + y_4 \leq 1$$

It can be noticed that the first and second rules ensure that only two values of x_i will be nonzero at a time. The last three rules ensure that the nonzero x_i will have to be adjacent. In literature, there is another way of linearizing the generator cost model as in [76], [171], and [181]. The model is explained through the equations below:

$$CG_{ct\omega\gamma} = C_c^{C,F} * u_{ct\omega\gamma}^C + \sum_{x=1}^{Nx} C_x^V * P_{ct\omega\gamma x}, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-176)$$

$$p_{ct\omega\gamma}^C = \underline{P}_c^C * u_{ct\omega\gamma}^C + \sum_{x=1}^{Nx} P_{ct\omega\gamma x}, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-177)$$

$$P_{ct\omega\gamma x} \leq p_x^V - p_{x-1}^V, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \forall x \in [2, Nx - 1] \quad (3-178)$$

$$P_{ct\omega\gamma x} \leq p_x^V - \underline{P}_c^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \forall x = [1] \quad (3-179)$$

$$P_{ct\omega\gamma x} \leq \bar{P}_c^C - p_{x-1}^V, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \forall x = [Nx] \quad (3-180)$$

$$P_{ct\omega\gamma x} \geq 0, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \forall x \in \Omega^x \quad (3-181)$$

Where $CG_{ct\omega\gamma}$ is the conventional generator running cost. The piecewise representation of the generator running cost is divided into blocks/segments, x , where each segment has a slope C_x^V and power produced $P_{ct\omega\gamma x}$. Finally, p_x^V is the upper limit of the power of block x .

The SOS2 is however better only in terms of the computational speed as explained in [182]. In this research, first, the SOS2 model is designed. Second, the speed of the SOS2 model and the model that is based on normal constraints will be compared.

3.14 Expanded Risk Averse Stochastic Programming Model

This model is adjusted to be more comprehensive in terms of combining all the possible constraints from all the aforementioned models. In addition, extra constraints will be added to make the model even more realistic.

3.14.1 Selected Stochastic DA Model with Risk

$$\max_{\Phi^{\text{DA},S}} \sum_{\omega \in \Pi^{\text{DA}}} \sum_{\gamma \in \Pi^{\text{RT}}} \pi_{\omega\gamma} \zeta_{\omega\gamma} + \beta \left[\rho - \frac{1}{1-\alpha} \sum_{\omega \in \Pi^{\text{DA}}} \sum_{\gamma \in \Pi^{\text{RT}}} \pi_{\omega\gamma} \mu_{\omega\gamma} \right] \quad (3-182)$$

$$\begin{aligned} \zeta_{\omega\gamma} = \sum_{t \in \Omega^{\text{T}}} & \left[\lambda_{t\omega\gamma}^{\text{DA}} p_{t\omega}^{\text{DA}} \Delta t + (\lambda_{t\omega\gamma}^{\text{DA}} + r_{t\omega\gamma}^{\text{RT}}) p_{t\omega\gamma}^{\text{RT}} \Delta t \right. \\ & + \sum_{d \in \Omega^{\text{D}}} U_{dt}^{\text{D}} p_{dt\omega\gamma}^{\text{D}} \Delta t - \sum_{c \in \Omega^{\text{C}}} \left(C_c^{\text{C,F}} u_{ct\omega\gamma}^{\text{C}} \Delta t + C_c^{\text{C,V}} \Delta t \right. \\ & \left. \left. + \bar{c}_{ct\omega\gamma}^{\text{C}} + \underline{c}_{ct\omega\gamma}^{\text{C}} \right) \right], \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \in \Pi^{\text{RT}} \end{aligned} \quad (3-183)$$

$$-\zeta_{\omega\gamma} + \rho - \mu_{\omega\gamma} \leq 0, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \in \Pi^{\text{RT}} \quad (3-184)$$

$$0 \leq \mu_{\omega\gamma}, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \in \Pi^{\text{RT}} \quad (3-185)$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega_n^D} p_{st\omega\gamma}^S - \sum_{\ell | S(\ell)=n} p_{\ell t\omega\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\omega\gamma}^L \\
& = p_{nt\omega\gamma}^M + \sum_{d \in \Omega_n^D} p_{dt\omega\gamma}^D, \forall n \in \Omega^M, \forall t \in \Omega^T, \forall \omega \\
& \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}}
\end{aligned} \tag{3-186}$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega_n^D} p_{st\omega\gamma}^S - \sum_{\ell | S(\ell)=n} p_{\ell t\omega\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\omega\gamma}^L \\
& = \sum_{d \in \Omega_n^D} p_{dt\omega\gamma}^D, \forall n \in \Omega^N \setminus n \in \Omega^M, \forall t \in \Omega^T, \forall \omega \\
& \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}}
\end{aligned} \tag{3-187}$$

$$p_{t\omega}^{\text{DA}} + p_{t\omega\gamma}^{\text{RT}} = \sum_{n \in \Omega^M} p_{nt\omega\gamma}^M, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \tag{3-188}$$

$$\begin{aligned}
p_{\ell t\omega\gamma}^L & = B_\ell(\delta_{s(\ell)t\omega\gamma} - \delta_{r(\ell)t\omega\gamma}), \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega \\
& \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}}
\end{aligned} \tag{3-189}$$

$$-\bar{P}_\ell^L \leq p_{\ell t\omega\gamma}^L \leq \bar{P}_\ell^L, \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \tag{3-190}$$

$$\delta_{nt\omega\gamma} = 0, n: \text{ref.}, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \tag{3-191}$$

$$-\pi \leq \delta_{nt\omega\gamma} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \tag{3-192}$$

$$\underline{P}^V \leq p_{t\omega}^{DA} \leq \bar{P}^V, \forall t \in \Omega^T \quad (3-193)$$

$$\underline{P}^V \leq p_{t\omega}^{DA} + p_{t\omega\gamma}^{RT} \leq \bar{P}^V, \forall t \in \Omega^T, \forall \omega, \forall \gamma \Pi^{RT} \quad (3-194)$$

$$-\bar{P}_n^M \leq p_{nt\omega\gamma}^M \leq \bar{P}_n^M, \forall n \in \Omega^M, \forall t \in \Omega^D, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (3-195)$$

$$\sum_{t \in \Omega^T} p_{dt\omega\gamma}^D \Delta t \geq \underline{E}_d^D, \forall d \in \Omega^D, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (3-196)$$

$$\underline{P}_{dt}^D \leq p_{dt\omega\gamma}^D \leq \bar{P}_{dt}^D, \forall d \in \Omega^D, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (3-197)$$

$$\begin{aligned} -R_d^{D,D} \Delta t \leq p_{dt\omega\gamma}^D - p_{d(t-1)\omega\gamma}^D \leq R_d^{D,U} \Delta t, \forall d \in \Omega^D, \forall t \in \Omega^T, \forall \omega \\ \in \Pi^{DA}, \forall \gamma \Pi^{RT} \end{aligned} \quad (3-198)$$

$$\underline{P}_c^C u_{ct\omega\gamma}^C \leq p_{ct\omega\gamma}^C \leq \bar{P}_c^C u_{ct\omega\gamma}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (3-199)$$

$$\begin{aligned} -R_c^{C,D} \Delta t \leq p_{ct\omega\gamma}^C - p_{c(t-1)\omega\gamma}^C \leq R_c^{C,U} \Delta t, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \\ \in \Pi^{DA}, \forall \gamma \Pi^{RT} \end{aligned} \quad (3-200)$$

$$\bar{C}_c^C (u_{ct\omega\gamma}^C - u_{c(t-1)\omega\gamma}^C) \leq \bar{c}_{ct\omega\gamma}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-201)$$

$$0 \leq \bar{c}_{ct\omega\gamma}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-202)$$

$$\underline{c}_c^C(u_{c(t-1)\omega\gamma}^C - u_{ct\omega\gamma}^C) \leq \underline{c}_{ct\omega\gamma}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-203)$$

$$0 \leq \underline{c}_{ct\omega\gamma}^C \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma, \quad (3-204)$$

$$e_{st\omega\gamma}^S = e_{s(t-1)\omega\gamma}^S + \eta_s^{S,C} p_{st\omega\gamma}^{S,C} \Delta t - \frac{p_{st\omega\gamma}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega$$

$$\in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-205)$$

$$\underline{E}_{st}^S \leq e_{st\omega\gamma}^S \leq \overline{E}_{st}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-206)$$

$$0 \leq p_{st\omega\gamma}^{S,C} \leq \overline{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-207)$$

$$0 \leq p_{st\omega\gamma}^{S,D} \leq \overline{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-208)$$

$$p_{st\omega\gamma}^S = p_{st\omega\gamma}^{S,D} - p_{st\omega\gamma}^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-209)$$

$$0 \leq p_{rt\omega\gamma}^R \leq \overline{P}_{rt\omega\gamma}^{R,A}, \forall r \in \Omega^R, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-210)$$

$$p_{t\omega}^{DA} \leq p_{t\omega'}^{DA}, \text{ if } \lambda_{t\omega}^{DA} \leq \lambda_{t\omega'}^{DA}, \forall t \in \Omega^T, \forall \omega, \forall \omega' \quad (3-211)$$

$$p_{t\omega}^{DA} = p_{t\omega'}^{DA}, \text{ if } \lambda_{t\omega}^{DA} = \lambda_{t\omega'}^{DA}, \forall t \in \Omega^T, \forall \omega, \forall \omega' \quad (3-212)$$

$$\begin{aligned}
c_{ct\omega\gamma}^{C,V,F} = & 824 p_{ct\omega\gamma 1}^C + 1463 p_{ct\omega\gamma 2}^C + 1972 p_{ct\omega\gamma 3}^C + 2804 p_{ct\omega\gamma 4}^C + \\
& 3504 p_{ct\omega\gamma 5}^C + 4235 p_{ct\omega\gamma 6}^C + 4991 p_{ct\omega\gamma 7}^C + 5765 p_{ct\omega\gamma 8}^C + \\
& 6566 p_{ct\omega\gamma 9}^C + 7394 p_{ct\omega\gamma 10}^C + 8324 p_{ct\omega\gamma 11}^C, \forall c \in \Omega^C, \forall t \in \\
& \Omega^T, \forall \omega, \forall \gamma
\end{aligned} \tag{3-213}$$

$$\begin{aligned}
p_{ct\omega\gamma}^C = & 112 p_{ct\omega\gamma 1}^C + 130 p_{ct\omega\gamma 2}^C + 148 p_{ct\omega\gamma 3}^C + 166 p_{ct\omega\gamma 4}^C \\
& + 184 p_{ct\omega\gamma 5}^C + 202 p_{ct\omega\gamma 6}^C + 220 p_{ct\omega\gamma 7}^C \\
& + 238 p_{ct\omega\gamma 8}^C + 256 p_{ct\omega\gamma 9}^C + 274 p_{ct\omega\gamma 10}^C \\
& + 294 p_{ct\omega\gamma 11}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma
\end{aligned} \tag{3-214}$$

$$\begin{aligned}
1 * u_{ct\omega\gamma}^C = & p_{ct\omega\gamma 1}^C + p_{ct\omega\gamma 2}^C + p_{ct\omega\gamma 3}^C + p_{ct\omega\gamma 4}^C + p_{ct\omega\gamma 5}^C + p_{ct\omega\gamma 6}^C \\
& + p_{ct\omega\gamma 7}^C + p_{ct\omega\gamma 8}^C + p_{ct\omega\gamma 9}^C + p_{ct\omega\gamma 10}^C + p_{ct\omega\gamma 11}^C, \forall c \\
& \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma
\end{aligned} \tag{3-215}$$

$$y_{ct\omega\gamma i} \geq p_{ct\omega\gamma i}^C, \forall i = [1 \text{ to } 11], \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma \tag{3-216}$$

$$\sum_i y_{ct\omega\gamma i} \leq 2, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma \tag{3-217}$$

$$y_{ct\omega\gamma i} + y_{ct\omega\gamma(i+m)} \leq 1, \quad m \geq 2, \forall i, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma \tag{3-218}$$

$$p_{ct\omega\gamma i}^c \geq 0, \forall i, \forall c \in \Omega^c, \forall t \in \Omega^T, \forall \omega, \forall \gamma \quad (3-219)$$

$$y_{ct\omega\gamma i} \text{ are binary } \forall i \quad (3-220)$$

It must be noted that equations (3-213) to (3-220) are specifically design based on the input data presented in the next chapters.

3.14.2 Selected Stochastic RT Model with Risk

$$\max_{\Phi^{RT,S}} \sum_{\gamma \in \Pi^{RT}} \pi_{\gamma} \zeta_{\gamma} + \beta \left[\rho - \frac{1}{1-\alpha} \sum_{\gamma \in \Pi^{RT}} \pi_{\gamma} \mu_{\gamma} \right] \quad (3-221)$$

$$\begin{aligned} \zeta_{\gamma} = \sum_{t \in \Omega^T} & \left[(\lambda_{t\gamma}^{DA} + r_{t\gamma}^{RT}) p_{t\gamma}^{RT} \Delta t \right. \\ & \left. + \sum_{d \in \Omega^D} U_{dt}^D p_{dt\gamma}^D \Delta t - \sum_{c \in \Omega^c} \left(C_c^{C,V,F} \Delta t + \bar{c}_{ct\gamma}^C + \underline{c}_{ct\gamma}^C \right) \right], \forall \omega \\ & \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \end{aligned} \quad (3-222)$$

$$-\zeta_{\gamma} + \rho - \mu_{\gamma} \leq 0, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-223)$$

$$0 \leq \mu_{\gamma}, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (3-224)$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\gamma}^L \\
& = p_{nt\gamma}^M + \sum_{d \in \Omega_n^D} p_{dt\gamma}^D, \forall n \in \Omega^M, \forall t \geq \tau, \forall \gamma,
\end{aligned} \tag{3-225}$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\gamma}^L \\
& = \sum_{d \in \Omega_n^D} p_{dt\gamma}^D, \forall n \in \Omega^N \setminus n \in \Omega^M, \forall t \geq \tau, \forall \gamma,
\end{aligned} \tag{3-226}$$

$$\tilde{p}_t^{\text{DA}} + p_{t\gamma}^{\text{RT}} = \sum_{n \in \Omega^M} p_{nt\gamma}^M, \forall t \geq \tau, \forall \gamma, \tag{3-227}$$

$$p_{\ell t\gamma}^L = B_\ell(\delta_{s(\ell)t\gamma} - \delta_{r(\ell)t\gamma}), \forall \ell \in \Omega^L, \forall t \geq \tau, \forall \gamma, \tag{3-228}$$

$$-\bar{P}_\ell^L \leq p_{\ell t\gamma}^L \leq \bar{P}_\ell^L \quad \forall \ell \in \Omega^L, \forall t \geq \tau, \forall \gamma \tag{3-229}$$

$$\delta_{nt\gamma} = 0, n: \text{ref.}, \forall t \geq \tau, \forall \gamma, \tag{3-230}$$

$$-\pi \leq \delta_{nt\gamma} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \geq \tau, \forall \gamma, \tag{3-231}$$

$$\underline{P}^V \leq \tilde{p}_t^{\text{DA}} + p_{t\gamma}^{\text{RT}} \leq \bar{P}^V, \forall t \geq \tau \tag{3-232}$$

$$-\bar{P}_n^M \leq p_{nt\gamma}^M \leq \bar{P}_n^M, \forall n \in \Omega^M, \forall t \geq \tau, \forall \gamma, \quad (3-233)$$

$$\sum_{t=1}^{\tau-1} \tilde{p}_{dt}^D \Delta t + \sum_{t=\tau}^{|\Omega^T|} p_{dt\gamma}^D \Delta t \geq \underline{E}_d^D, \forall d \in \Omega^D, \forall \gamma, \quad (3-234)$$

$$\underline{P}_{dt}^D \leq p_{dt\gamma}^D \leq \bar{P}_{dt}^D, \forall d \in \Omega^D, \forall t \geq \tau, \forall \gamma, \quad (3-235)$$

$$-R_d^{D,D} \Delta t \leq p_{dt\gamma}^D - p_{d(t-1)\gamma}^D \leq R_d^{D,U} \Delta t, \forall d \in \Omega^D, \forall t \geq \tau, \forall \gamma, \quad (3-236)$$

$$\underline{P}_c^C u_{ct\gamma}^C \leq p_{ct\gamma}^C \leq \bar{P}_c^C u_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-237)$$

$$-R_c^{C,D} \Delta t \leq p_{ct\gamma}^C - p_{c(t-1)\gamma}^C \leq R_c^{C,U} \Delta t, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-238)$$

$$\bar{C}_c^C (u_{ct\gamma}^C - u_{c(t-1)\gamma}^C) \leq \bar{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-239)$$

$$0 \leq \bar{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-240)$$

$$\underline{C}_c^C (u_{c(t-1)\gamma}^C - u_{ct\gamma}^C) \leq \underline{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-241)$$

$$0 \leq \underline{c}_{ct\gamma}^C \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \quad (3-242)$$

$$e_{st\gamma}^S = e_{s(t-1)\gamma}^S + \eta_s^{S,C} p_{st\gamma}^{S,C} \Delta t - \frac{p_{st\gamma}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-243)$$

$$\underline{E}_{st}^S \leq e_{st\gamma}^S \leq \bar{E}_{st}^S, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-244)$$

$$0 \leq p_{st\gamma}^{S,C} \leq \bar{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-245)$$

$$0 \leq p_{st\gamma}^{S,D} \leq \bar{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \quad (3-246)$$

$$p_{st\gamma}^S = p_{st\gamma}^{S,D} - p_{st\gamma}^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma \quad (3-247)$$

$$0 \leq p_{rt\gamma}^R \leq \bar{P}_{rt\gamma}^{R,A}, \forall r \in \Omega^R, \forall t = \tau, \forall \gamma \quad (3-248)$$

$$0 \leq p_{rt\gamma}^R \leq P_{rt\gamma}^{R,A}, \forall r \in \Omega^R, \forall t > \tau, \forall \gamma \quad (3-249)$$

$$p_{t\gamma}^{RT} \leq p_{t\gamma'}^{RT}, \quad \text{if } \lambda_{t\gamma}^{RT} \leq \lambda_{t\gamma'}^{RT}, \forall t \in \Omega^T, \forall \gamma, \forall \gamma' \quad (3-250)$$

$$p_{t\gamma}^{RT} = p_{t\gamma'}^{RT}, \quad \text{if } \lambda_{t\gamma}^{RT} = \lambda_{t\gamma'}^{RT}, \forall t \in \Omega^T, \forall \gamma, \forall \gamma' \quad (3-251)$$

$$\begin{aligned}
c_{ct\gamma}^{C,V,F} = & 824 p_{ct\gamma 1}^C + 1463 p_{ct\gamma 2}^C + 1972 p_{ct\gamma 3}^C + 2804 p_{ct\gamma 4}^C + \\
& 3504 p_{ct\gamma 5}^C + 4235 p_{ct\gamma 6}^C + 4991 p_{ct\gamma 7}^C + 5765 p_{ct\gamma 8}^C + 6566 p_{ct\gamma 9}^C + \\
& 7394 p_{ct\gamma 10}^C + 8324 p_{ct\gamma 11}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega, \forall \gamma
\end{aligned} \tag{3-252}$$

$$\begin{aligned}
p_{ct\omega\gamma}^C = & 112 p_{ct\gamma 1}^C + 130 p_{ct\gamma 2}^C + 148 p_{ct\gamma 3}^C + 166 p_{ct\gamma 4}^C + 184 p_{ct\gamma 5}^C \\
& + 202 p_{ct\gamma 6}^C + 220 p_{ct\gamma 7}^C + 238 p_{ct\gamma 8}^C + 256 p_{ct\gamma 9}^C \\
& + 274 p_{ct\gamma 10}^C + 294 p_{ct\gamma 11}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma
\end{aligned} \tag{3-253}$$

$$\begin{aligned}
1 * u_{ct\gamma}^C = & p_{ct\gamma 1}^C + p_{ct\gamma 2}^C + p_{ct\gamma 3}^C + p_{ct\gamma 4}^C + p_{ct\gamma 5}^C + p_{ct\gamma 6}^C + p_{ct\gamma 7}^C + p_{ct\gamma 8}^C \\
& + p_{ct\gamma 9}^C + p_{ct\gamma 10}^C + p_{ct\gamma 11}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma
\end{aligned} \tag{3-254}$$

$$y_{ct\gamma i} \geq p_{ct\gamma i}^C, \forall i = [1 \text{ to } 11], \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \tag{3-255}$$

$$\sum_i y_{ct\gamma i} \leq 2, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \tag{3-256}$$

$$y_{ct\gamma i} + y_{ct\gamma(i+m)} \leq 1, \quad m \geq 2, \forall i, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \tag{3-257}$$

$$p_{ct\gamma i}^C \geq 0 \quad \forall i, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \tag{3-258}$$

$$y_{ct\gamma i} \text{ are binary } \forall i \tag{3-259}$$

CHAPTER 4

METHODOLOGY

4.1 Methodology

The research starts by presenting a background onto the topic of virtual power plants. The background will talk about the topic as a whole, practical cases, statistical data, and the components of the VPP in general. It will also address the future plans/policies and how they highlight the importance of VPPs. In addition, how different control strategies can affect the profit and the structure as well as the components of the VPP. After that, the motivation of this research is addressed where it will be set clear why this topic is of a great interest.

Different objectives are highlighted which relate to the topologies of VPPs, control strategies, optimization techniques, single and multi-objective optimization, and system design. The objectives, background, motivation, and introduction are all based on an extensive literature review that is done before, during, and even after the preparation of these sections. The literature review starts by defining the VPP, and by discussing each component of it and how different researchers select their design with some of these components. It also shows the advantages and disadvantages of each topology and the difficulty that comes with each topology.

A research proposal is made based on the above points and the research methodology is set too. The virtual power plant system would be designed, the problem will as well be formulated. Different optimization techniques and models will be presented and some will be applied onto the designed VPP model. Next, the optimization problem is going to be solved in order to achieve the required objective functions. Multi-objective optimization problems are to be examined. After that, simulations of the optimization problem of the VPP will be carried out to eventually reach the discussion onto the findings.

Conclusions can be drawn based on the aforementioned sequence where publications are as well to be made along with the submission of the final draft of the research in preparation to the defense. The methodology of this research is summarized in Figure 4-1 and Figure 4-2.

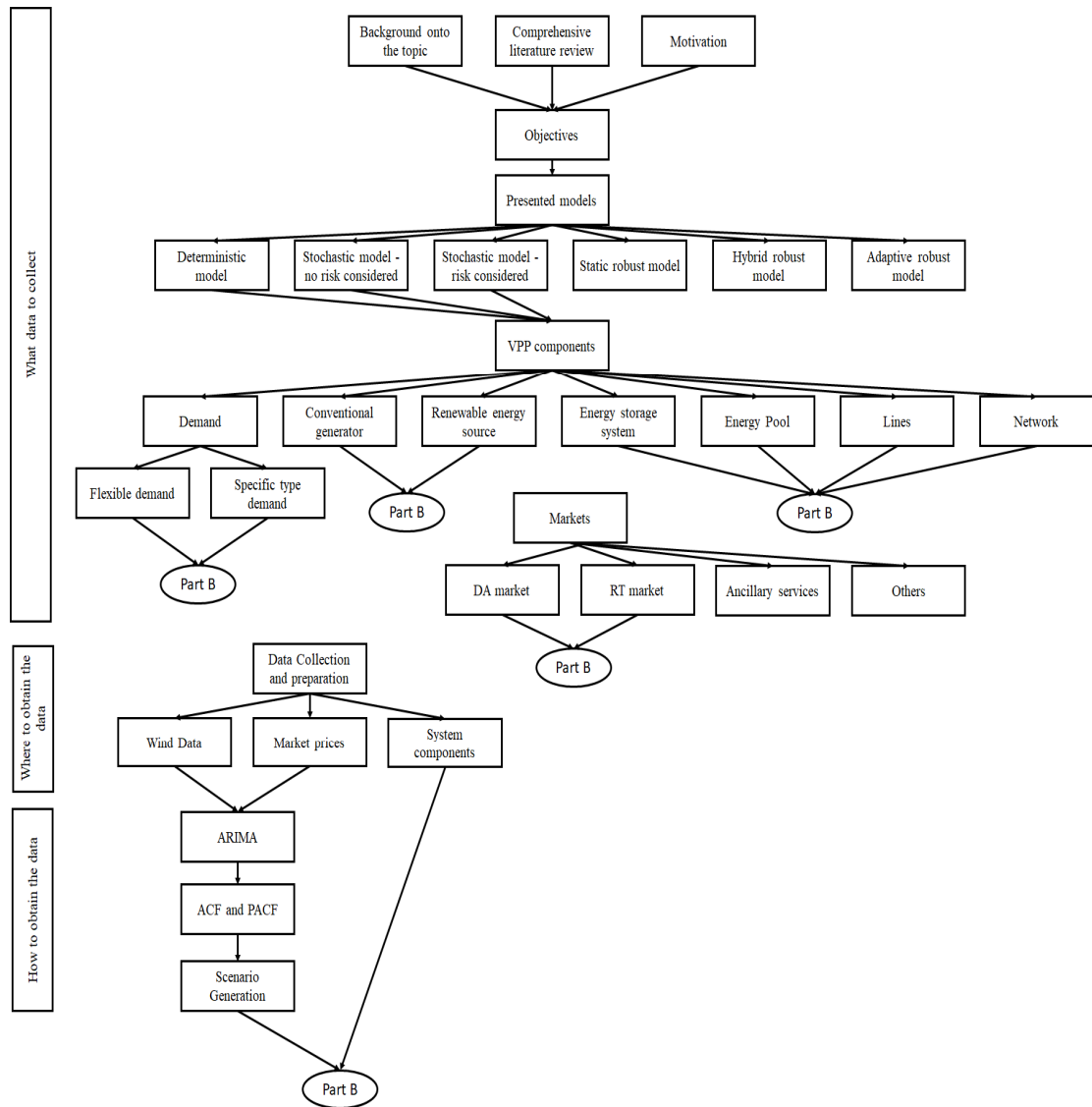


Figure 4-1 Methodology flowchart

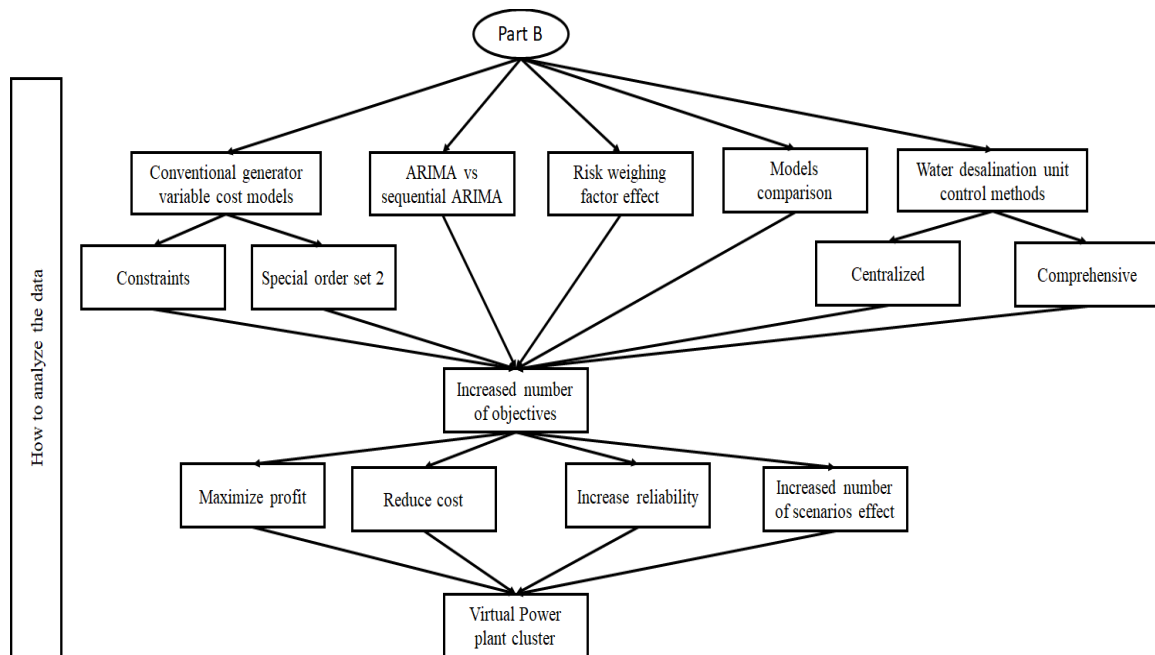


Figure 4-2 Methodology flowchart

As seen from the figures above, first, a comprehensive literature review is made on the topic of virtual power plants, a background onto the topic is provided and the motivation behind the selection of the topic is presented as well. Based on this theoretical research, the objectives of this research are set. Based on these objectives, the linear programming models in literature that are used to represent virtual power plants are studied and the most suitable one is selected. Since robust optimization techniques are very conservative, they have not been selected. Stochastic optimization, though can be computationally demanding, is better in terms of balance between conservativeness and comprehensiveness. This is why only the stochastic and deterministic models are selected for the rest of the research.

The components of a virtual power plant (VPP) are selected such that the VPP has both dispatchable and non-dispatchable units. The VPP has demand which is divided into flexible demand and specific type demand (water desalination unit). It has renewable energy resources which is represented by a wind power generator. It also has a conventional generator, and an energy storage system. Of course, the network and the lines are part of the structure of the VPP. There is another important component which will be elaborated onto at a later stage which is the energy pool. By this, the optimization/ solution methods have been selected and the system components have been prepared as well. The last part of the data collection section is the market part. There are different markets that can be studied such as the day-ahead market where bidding is done for the next 24 hours, the real-time market where bidding is done on hourly basis, the ancillary services market where voltage, frequency quality and other services are maintained, and there are other energy trading platforms such as future contracts. As it is a very big scope to consider all of them in this research, the first and the most major two bidding markets are selected. These are the day-ahead and real-time markets.

The next part is obtaining the data. As the system has been prepared with the solution methods in the previous part, the input data to the system must be carefully prepared for the accuracy of simulation, analysis, and results. There are three uncertain parameters which are the day-ahead market prices, real-time market prices, and the wind speed data. This data was selected to be for the same electricity market region, same geographical location, and the same time period. The data is selected from trusted references or the market operators themselves.

The wind data was obtained from [173] while the market prices were obtained from [172]. The geographical location for the locational marginal prices is Worcester, MA, USA and the geographical location for the wind data is Paxton which is the closest area to Worcester where wind data is available. The historical data is considered for year 2011. The forecasted day will be the 23rd of May 2011. The year 2011 is selected as it is the latest year at [172] and [173] at which the data of the three uncertain parameters is fully available.

There are other system components such as the demand and generator where data is also required. This data is however not part of the uncertain data category and thus it is obtained from the literature as noted reference-wise. In regard to the markets, the market where Paxton and Worcester exist is NE-ISO. The ISO of New England, USA is responsible for all the planning, administration, contract management, and electricity markets of six states. Those six states are Massachusetts, Vermont, Connecticut, New Hampshire, Maine and Rhode Island. The state considered is Massachusetts.

The last part shown on Figure 4-1 is the data pre-processing and preparation part. After obtaining the data as per the previous section, it must be pre-processed. For example, the uncertain parameters must be forecasted. After that, the wind speed has to be converted to wind power. Scenario generation is also required for stochastic models. First, the autoregressive moving average (ARIMA) method is used for forecasting the future data which is the 24 hours scope of the study. An ARIMA model must be designed in order to do the forecast. Constructing an accurate ARIMA model requires not only knowledge but some

experience as some tools and methods are needed for the evaluation of the model such as the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Next, once an ARIMA model is designed and the data is forecasted and tested for accuracy using suitable evaluation methods such as the mean square error (MSE), scenario generation can be done. Scenario generation can be done through the use of Monte Carlo Simulation (MCS).

The second part of the methodology which is shown on Figure 4-2 is about the simulation and analysis. Since the model and the data have been prepared as explained above, the system can now be simulated and tested. In order to prove the effectiveness of the proposed system, structure, and methodology, some evaluation processes are applied. After the system is simulated, the deterministic model, the stochastic model with no risk, and the stochastic model with risk are compared to show the advantages of the selection of the stochastic model with risk over the other choices.

Also, the sequential ARIMA model proposed to be used in the real-time market is compared to the conventional ARIMA model used in literature to prove the value addition introduced by the sequential ARIMA model. The risk consideration is done through the use of the conditional value at risk which has a weighing factor. The effect of changing this weight factor is also considered. The conventional generator piecewise linear function is modelled in literature through a set of constraints. In literature, it is claimed that using special order set type two (SOS2) solution method for piecewise linear functions is faster

than using constraints. Thus, it is proposed to design a SOS2 model and test it against the set of constraints for the evaluation and selection of the better model.

There is a specific type demand introduced which is the water desalination unit (WDU). It is included as the other loads of the system are and they all are included under a centralized control scheme. However, since the WDU has its own demand which is the water demand, it might be better to optimize its own objective as it is acting both as an electric load to the VPP but also as a generator to its water demanding customers. Therefore, a comprehensive control scheme is proposed where the WDU optimizes its own objective instead of following the centralized objective of the VPP.

The next step is to propose and introduce reliability constraints which help mitigate the incidences of failing to participate into the real-time electricity market when planning to participate. To prove the effectiveness of the reliability constraints, they are tested against the idea of increasing the number of scenarios. Increasing the number of scenarios means opening the chance for generating scenarios that might be worse or better. Having new worse scenarios in a risk considerate problem means a better chance to avoid those incidences of failure. Thus, it is compared to the proposed reliability constraints as a validation step.

Combining all the concepts above, a multi-objective problem can be formulated where profit maximization, cost reduction, and reliability are the multiple objectives. By this, a VPP is designed including variety of components, tested against different models and

prepared with reliable data. It also has multiple objectives and an important specific load such as the WDU. The last step is the introduction of an energy pool to the system and the design of a VPP cluster.

An energy pool is a big energy source that acts as a backup to the VPP. In literature, an energy pool is used with multiple microgrids as backup to the microgrids. There can be multiple AC or DC microgrids that are interconnected through an energy pool. The energy pool monitors the voltage of the DC bus of the DC microgrids and the frequency of the AC microgrids. Any variation from the nominal value indicates the need for the energy pool (EP) to interact to mitigate that imbalance. In VPPs, an EP is not discussed in literature as the VPP is already connected to the network and it does not work in an islanded mode to need an EP. This is not necessarily correct. As explained earlier, the VPP may fail to participate into the market at some hour which could cause power imbalance to the VPP. Thus, an EP can be connected to multiple VPPs making a VPP cluster. Therefore, a VPP cluster is designed, simulated, and analyzed. Lastly, conclusions are drawn onto all the steps taken above.

CHAPTER 5

CASE STUDIES AND SIMULATIONS

5.1 MILP Input Data

There are multiple components in the VPP as discussed in the previous chapters. Each component such as the renewable source generator, conventional generator, demand, storage, main grid, and network has its own parameters. To do the simulation, the data and constraints for each of those subsystems shall be collected.

5.1.1 Network and VPP Parameters

Figure 5-1 shows the network with all the components of the VPP including the main grid, which is connected to bus 1, [169]. The conventional generator has been added to the 4th bus as it was not part of the original network. The storage unit and the wind turbine generator are connected to the 5th bus while seven demands are connected to busses one to four. Those demands are comprised of multiple loads. Table A-1 shows the network data while Table A-2 and Table A-3 show the demand data, [169]. Table A-4 shows the base utility data. The hourly utility data can be derived from the base one based on the following criteria:

1. Demands 1 to 4 have a multiplication factor of 0.8, 1.0, 1.2 for hours 1 to 8, 9 to 16, and 17 to 24 respectively.
2. Demands 5 to 7 have a multiplication factor of 1.1, 0.9, 1.0 for hours 1 to 8, 9 to 16, and 17 to 24 respectively.

Based on these criteria, Table A-5, Table A-6, and Table A-7 can be obtained. The symbols on the tables are defined in the abbreviations section.

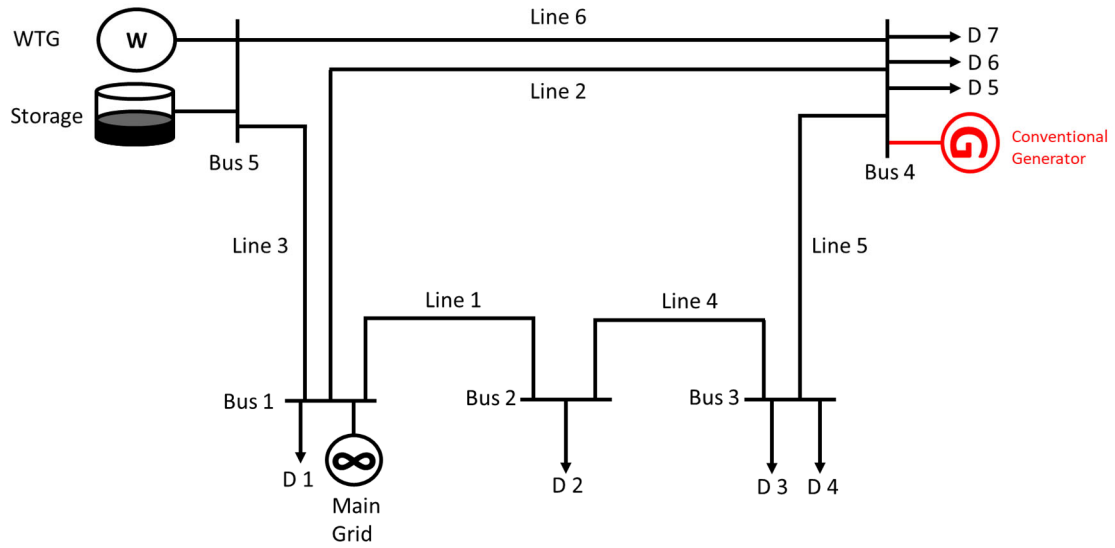


Figure 5-1 5-Bus network

The storage data is shown on Table A-8. The storage capacity, charging and discharging ramp rates are all provided. In addition to the initial energy state and the efficiency of charge/ discharge. The main grid and market data are summarized in Table A-9. The power exchange at the main grid node is a technical constraint while the power exchange with the Day-ahead and real-time markets is a constraint related to the market.

The conventional generator has been added to the network in order to expand it to diversify the components of the VPP. The information about the added conventional generator is summarized in Table A-10, [171].

The variable cost of the conventional is represented by a piecewise linear function as presented in Table A-11 Which can be formulated as a piecewise function as:

$$Gen. Cost = \begin{cases} 35.5P - 3152 & 112 \leq P \leq 130 \\ 36.5P - 3282 & 130 \leq P \leq 148 \\ 38P - 3504 & 148 \leq P \leq 166 \\ 39P - 3670 & 166 \leq P \leq 184 \\ 40.5P - 3946 & 184 \leq P \leq 202 \\ 42P - 4249 & 202 \leq P \leq 220 \\ 43P - 4469 & 220 \leq P \leq 238 \\ 44.5P - 4826 & 238 \leq P \leq 256 \\ 46P - 5210 & 256 \leq P \leq 274 \\ 46.5P - 5347 & 274 \leq P \leq 294 \end{cases} \quad (5-1)$$

Where P in (5-1) refers to the power generated by the conventional generator. The curve of this variable cost model is shown on Figure 5-3. It must be noted that this covers both the variable and fixed costs. Therefore, the objective function has to be adjusted accordingly.

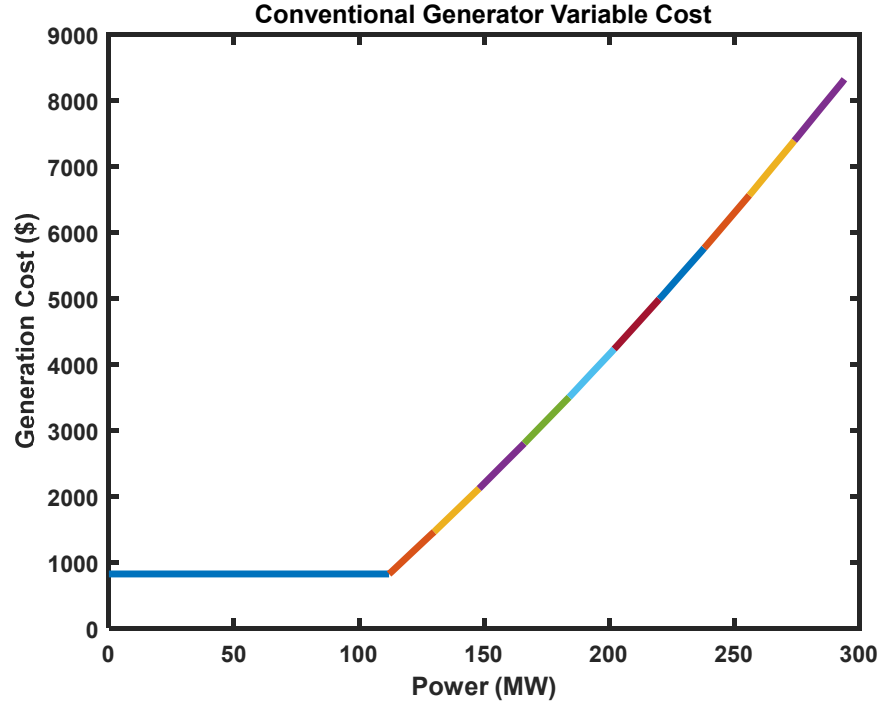


Figure 5-2 Conventional generator variable cost curve

The colored segment on Figure 5-2 is a piecewise linear function and each colored segment is a linear part.

5.1.2 Wind Power and Market Prices

The wind power, DA market prices, and RT market prices are to be represented through ARIMA models as explained in the previous sections/chapters. The historical market prices can be obtained from [172] while the wind turbine data can be obtained from [173]. The wind turbine considered is made of forty units each is 2.5-MW (model Nordex N80/2500 KW), [174]. The cut-in, rated, and cut-out speeds are 4, 17, and 25 m/s, respectively. The historical data is considered for year 2011. Based on the model, the historical data of 2011 from first of January until the end of the 22nd of May will be utilized. The forecasted day

will be the 23rd of May 2011. The locational marginal prices are related to Worcester, MA, USA. The wind data is taken at Paxton which is the closest area to Worcester where wind data is available. Thus, the prices and wind data are taken for the same location and same time in order for all the studied data to be realistic.

First, the DA market prices model will be explained in details, and the rest of the models will follow the same concept but not the same model. First, the historical data for the past three months will be considered. This will help avoiding seasonal data that is related to the weather when considering a longer time frame. However, daily seasonal correlation might still exist. First, the last three months DA market prices are plotted on Figure 5-3. Those are the 90 days before the considered day which is the 23rd of May 2011. It can be seen that the mean is not constant and thus transformation might be needed. If some points are equal to zero, log transformation will not be valid, but setting those points to 0.001 for example might solve this issue.

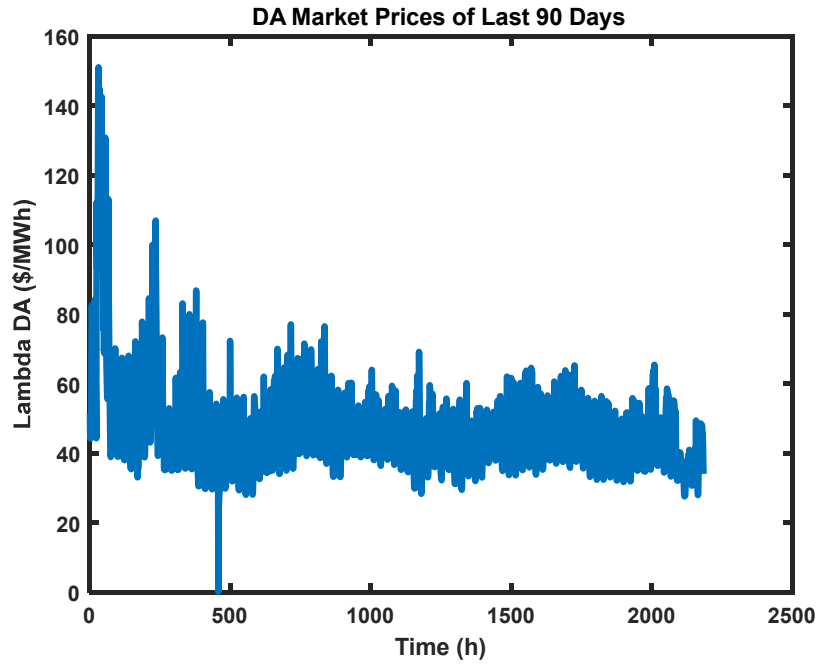


Figure 5-3 DA market prices (90 days)

Thus, a transformed series of the data will look like Figure 5-4. The data seem to be more stable with no obvious trend, volatility or seasonality. There could however be some daily seasonality that is not yet clear. Therefore, the ACF and PACF will be plotted for further analysis as explained in the previous sections/chapters.

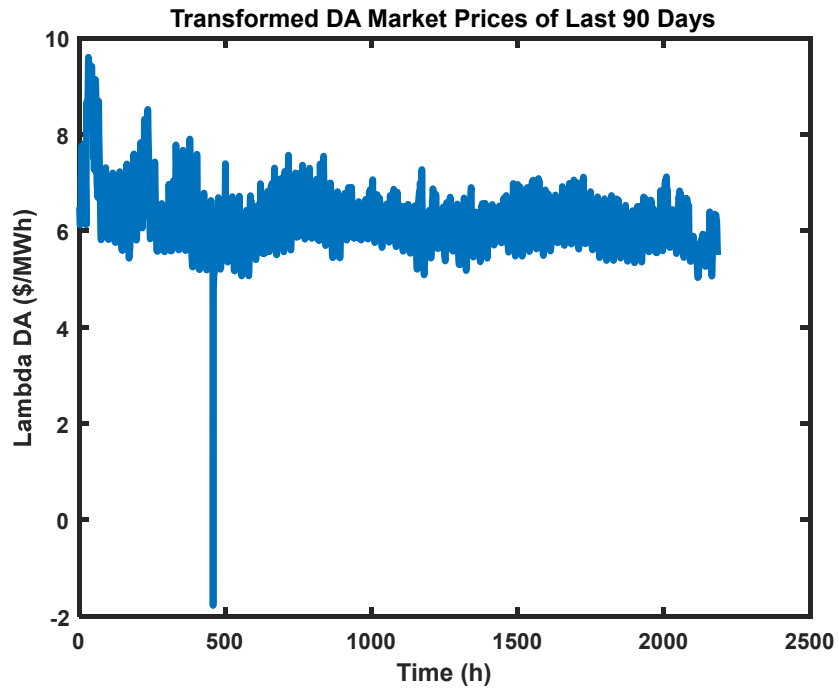


Figure 5-4 Transformed DA market prices (90 days)

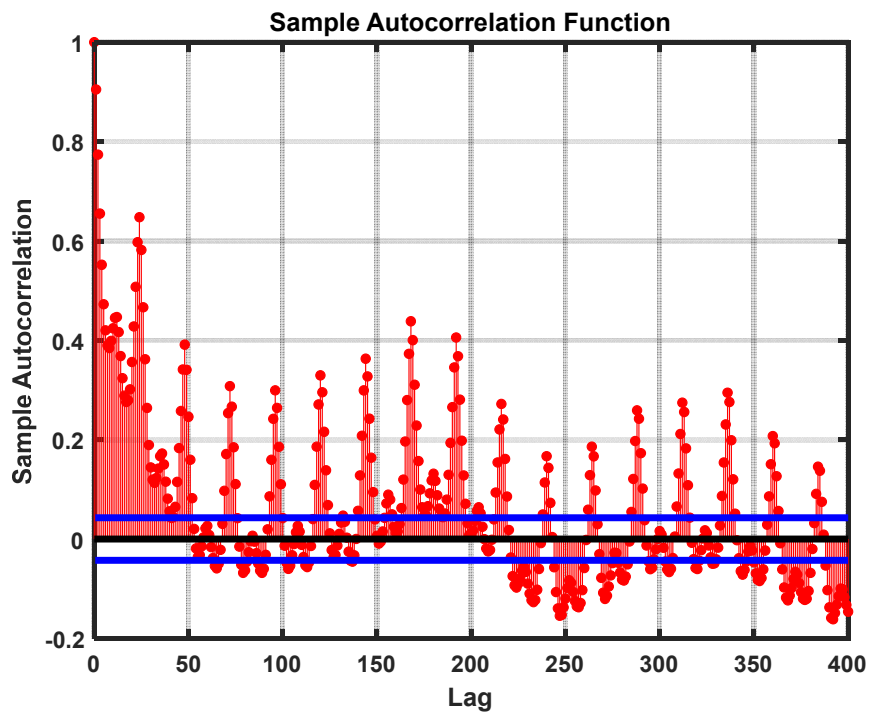


Figure 5-5 ACF DA market prices (90 days)

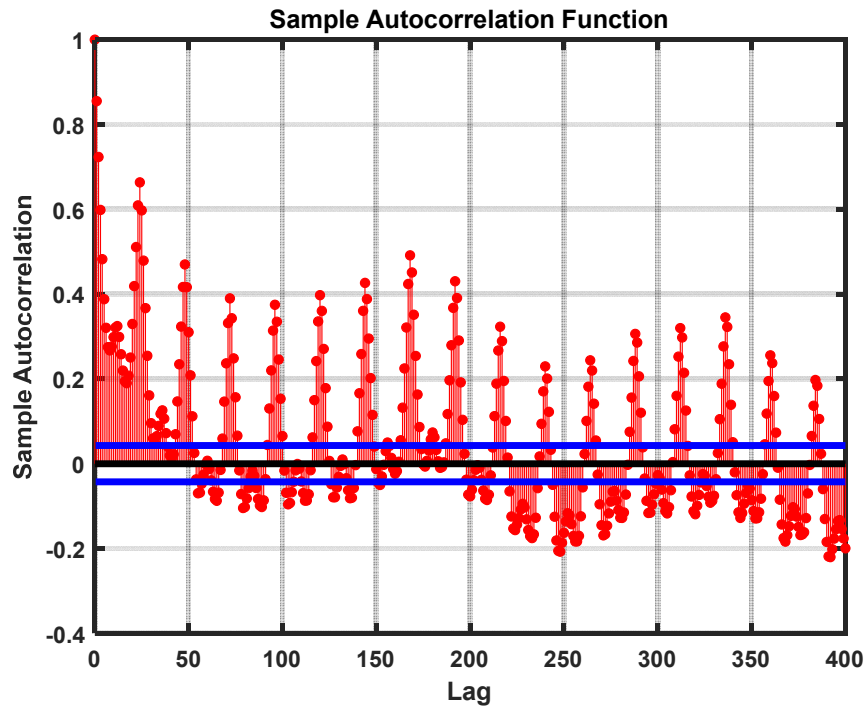


Figure 5-6 ACF transformed DA market prices (90 days)

It can be seen from Figure 5-5 and Figure 5-6 that the ACF for both the original and the transformed data is unstable. This might be a sign for a need of differencing. It can also be seen that there is a seasonality of 24 hours and thus, two differencing levels will be applied. One integration differencing and one seasonal differencing at 24 hours. If only integration differencing is done with a degree of one, the ACF will look as Figure 5-7. If, however, single degree differencing and seasonal differencing at 24 hours are applied, the ACF and the PACF will look as shown on Figure 5-8 and Figure 5-9 respectively.

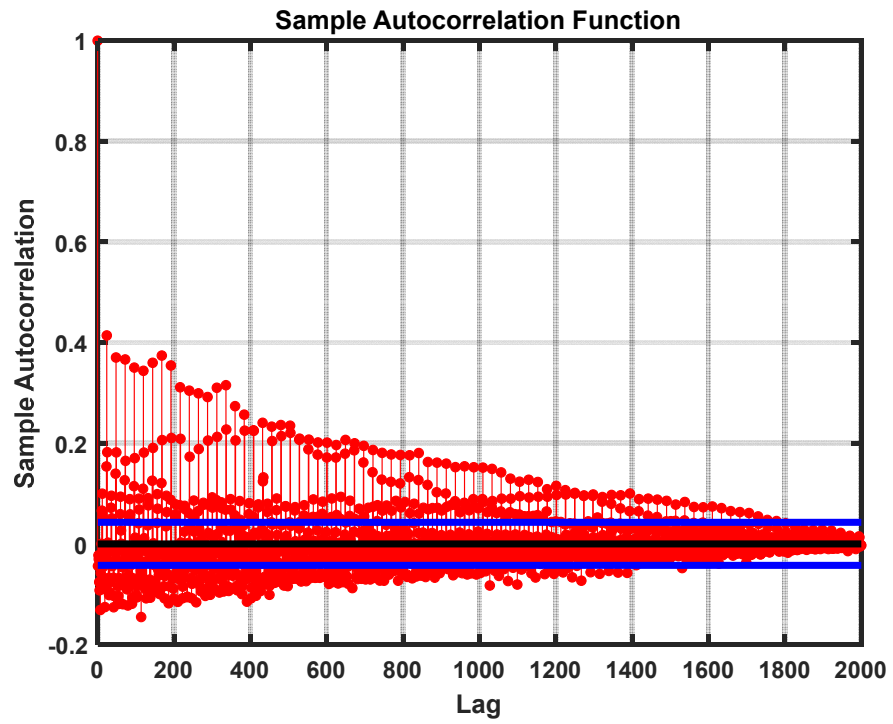


Figure 5-7 ACF differenced, transformed DA prices

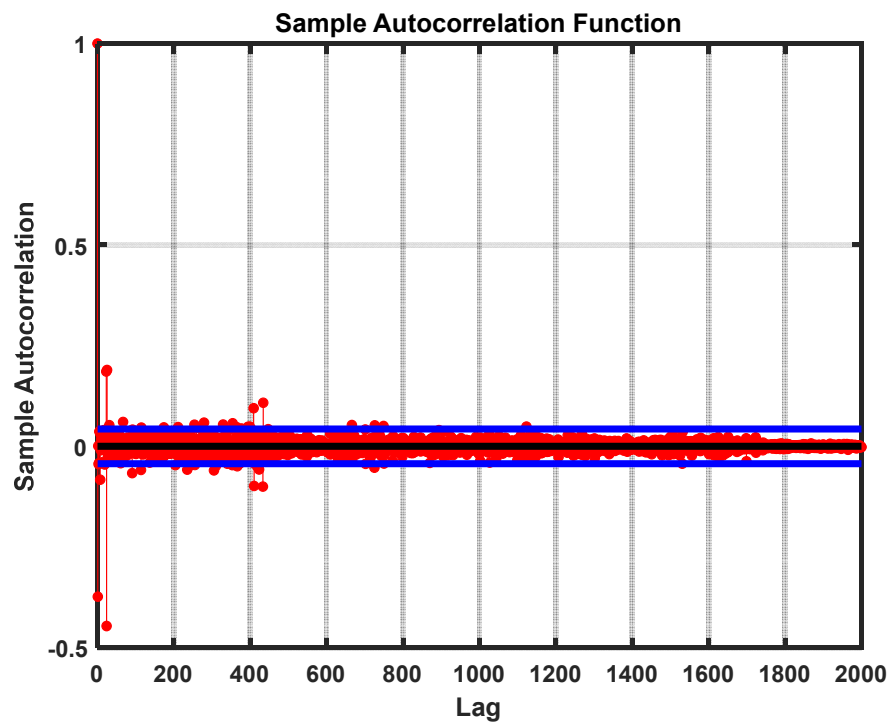


Figure 5-8 ACF differenced (seasonal + integration), transformed DA prices

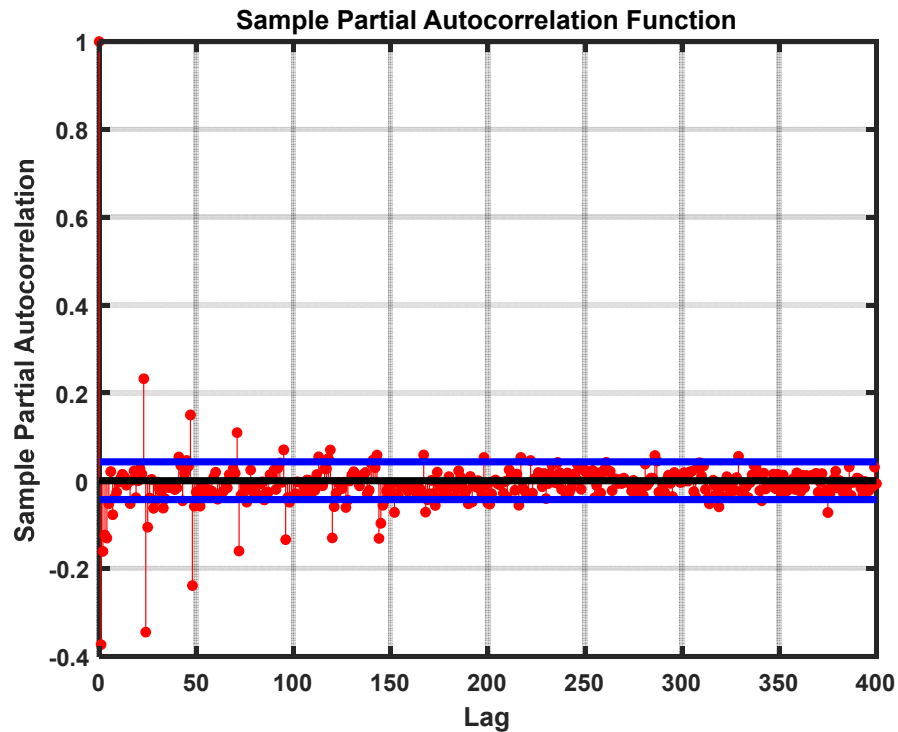


Figure 5-9 PACF differenced (seasonal + integration), transformed DA prices

It can be noticed that the ACF and PACF are now more stable with fewer obvious lags. On the PACF plot, the lags are at multiples of 23 and 24 hours. This can be considered as seasonal AR lags. The major significant lags on the ACF are at 23 and 24 hours and those can be considered as seasonal MA lags. After that, based on the BIC, the order of p and q can be selected. In this case, p was selected in the order of 2 and q in the order of 1. Since the model has been specified, the parameters can be estimated and therefore, the next 24 hours DA prices can be forecasted. Figure 5-10 shows the forecasted and actual prices of the 23rd of May 2011.

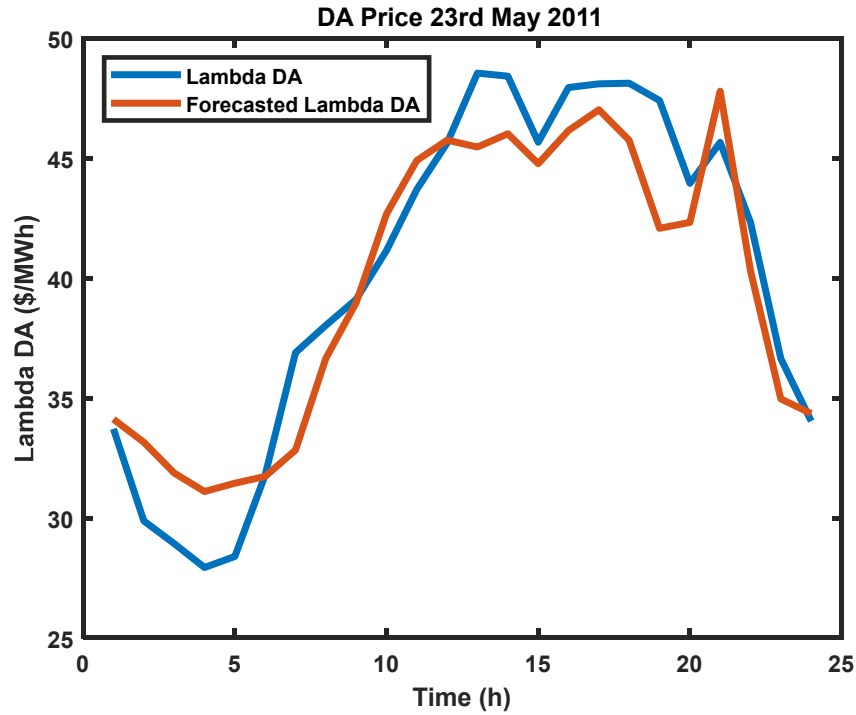


Figure 5-10 Actual and forecasted DA prices 23 May 2011

The same analysis shown above can be applied to the RT market prices and the wind speed or wind power forecast. The actual and forecasted figures of the RT market prices and the wind speed are shown on Figure 5-11 and Figure 5-12 respectively. The wind speed is less accurate as ARIMA is not very good for long term forecast (more than 10 hours) for data such as wind speed data due to its high volatility. ARIMAX could be used as an alternative in this case. However, the accuracy of this forecast is acceptable and thus, it will be considered in the rest of the analysis.

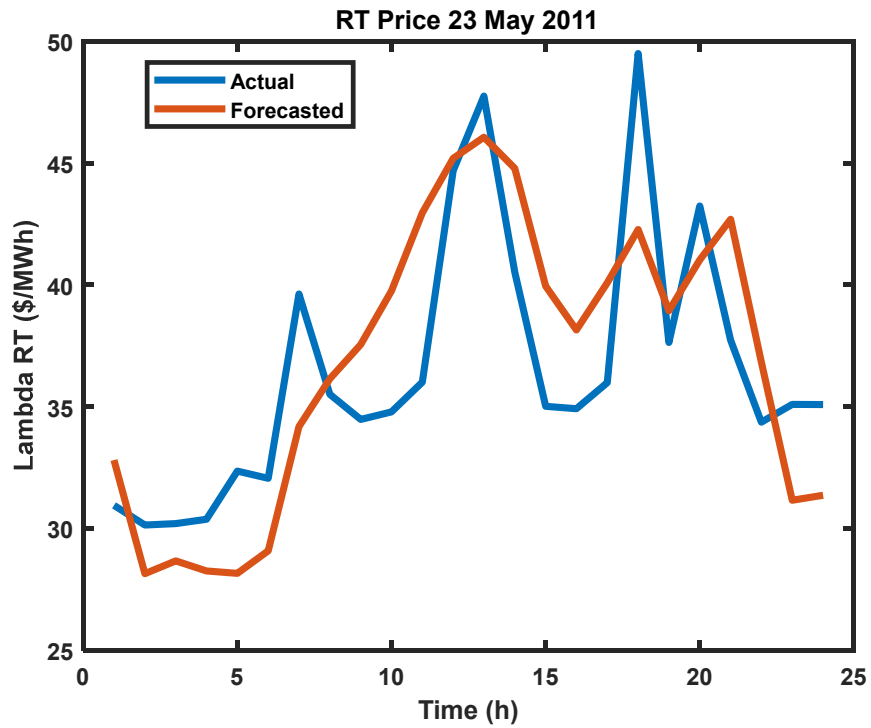


Figure 5-11 Actual and forecasted RT prices 23 May 2011

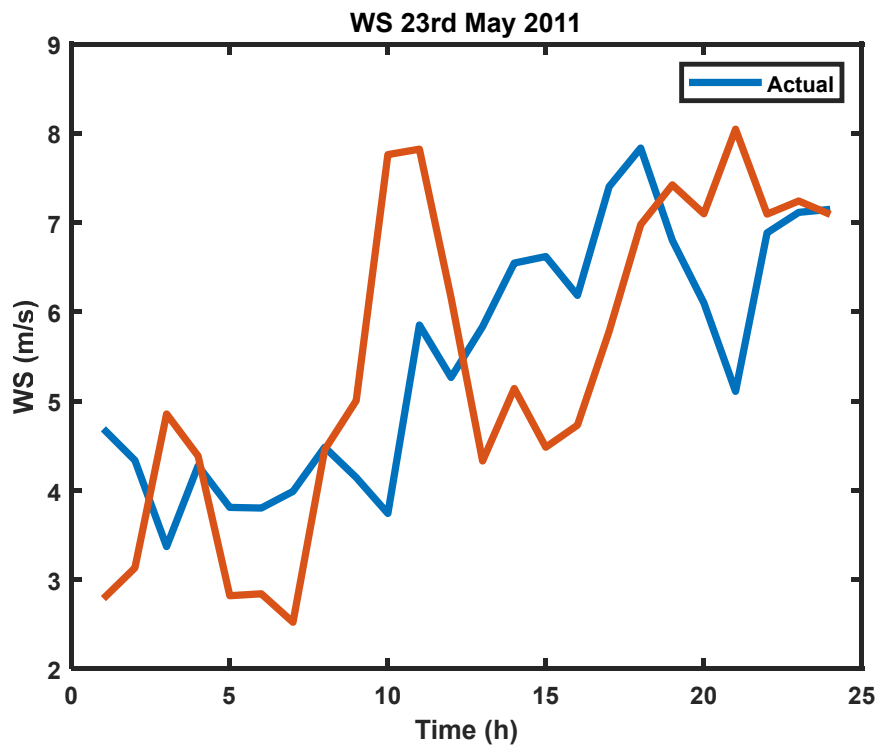


Figure 5-12 Actual and forecasted wind speed 23 May 2011

Multiple notes can be made here on the data shown above. First, the wind speed for the next 24 hours can be forecasted for the DA market model. However, for the RT model, it can be sequentially forecasted on hourly basis since in reality, the RT bidding is done on hourly basis. If this sequential forecasting model is applied, the output will look as shown on Figure 5-13. The same concept can be applied to the RT market prices as shown on Figure 5-14.

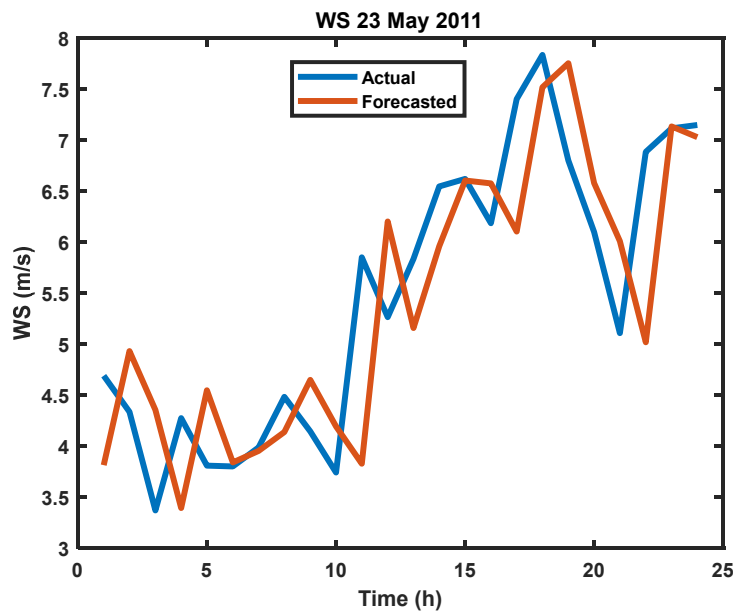


Figure 5-13 Actual and forecasted sequential wind speed 23 May 2011

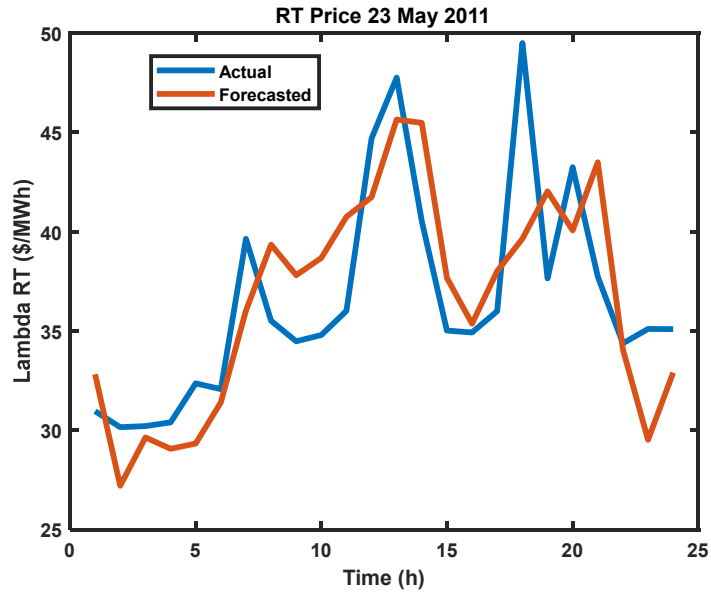


Figure 5-14 Actual and forecasted sequential RT market price 23 May 2011

Another note is that the real-time market prices are highly correlated to the day-ahead market prices. In order to avoid this high correlation and have independent variables in the model of study, the RT prices will not be considered. The difference between the Day-ahead and real-time prices which will be called the residual prices is going to replace the RT prices. This residual price can be forecasted for the next 24 hours as well as sequentially as shown on Figure 5-15 and Figure 5-16 respectively.

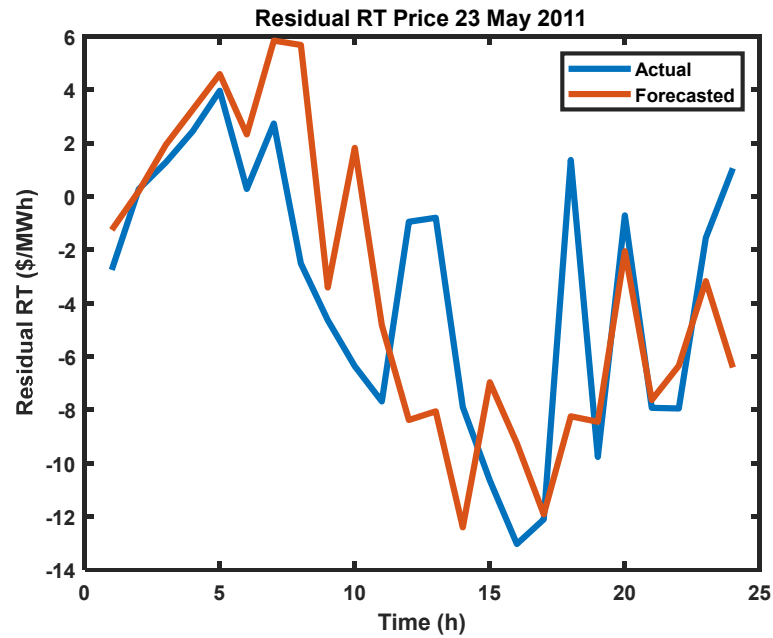


Figure 5-15 Actual and forecasted residual price 23 May 2011

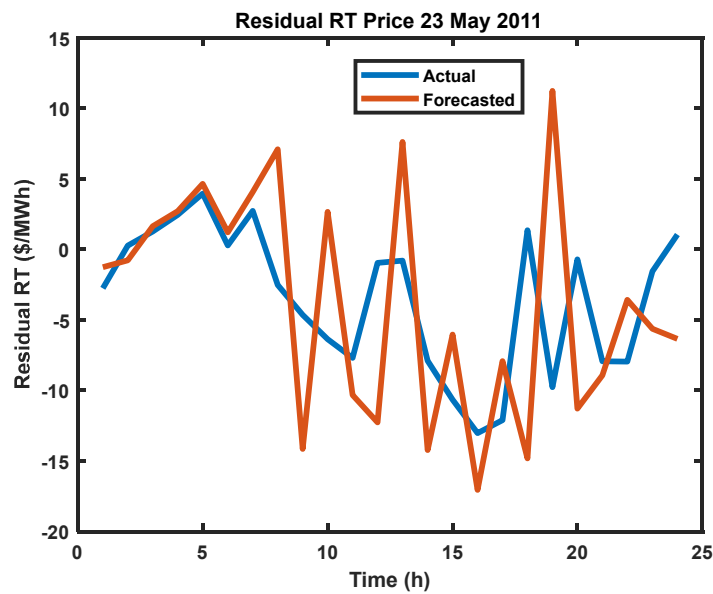


Figure 5-16 Actual and forecasted sequential residual price 23 May 2011

Lastly, for stochastic modelling, multiple scenarios should be considered. Therefore, based on the obtained SARIMA models, multiple scenarios should be forecasted. Based on the theories explained in the previous sections/chapters, forecasting can be done with a specific

number of scenarios. Five scenarios for each uncertain parameter will be considered. Figure 5-17 to Figure 5-19 show the five scenarios for each uncertain parameter namely wind speed, DA price and residual price respectively. Each of the five scenarios has a 20% probability. It must be noted that every time the model is run, the forecasted scenarios might be slightly different.

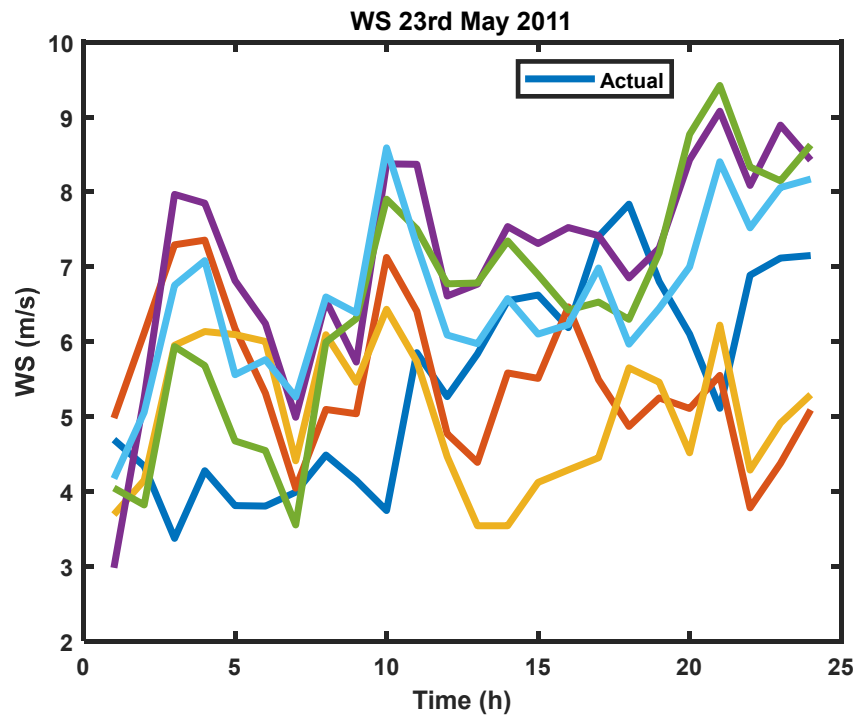


Figure 5-17 Five scenarios wind speed 23 May 2011

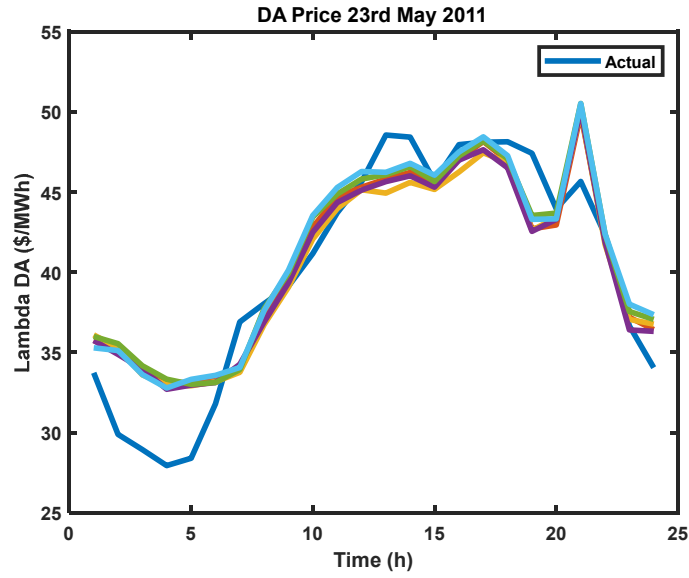


Figure 5-18 Five scenarios DA price 23 May 2011

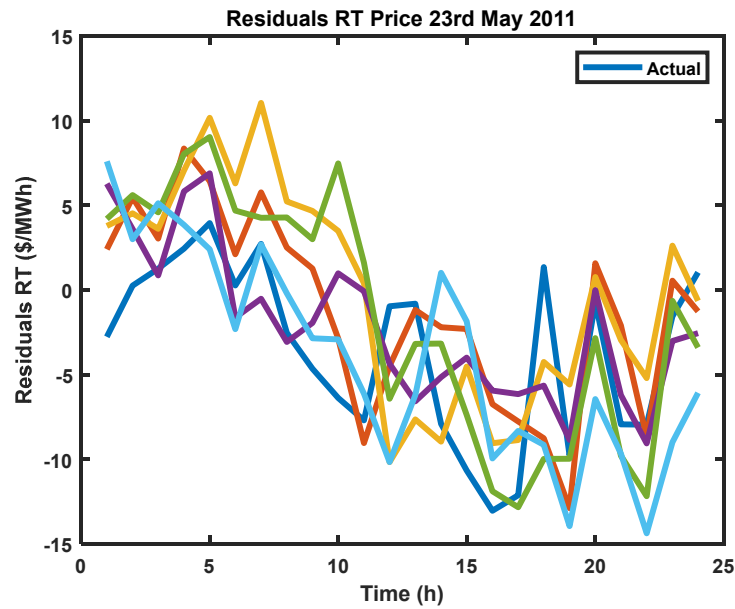


Figure 5-19 Five scenarios residual price 23 May 2011

5.1.3 DA Market Scenarios Data

The components of the VPP have been modeled and the data related to each model has been presented. The data related to the possible scenarios and how they evolve/change each

hour are placed into separate sections. In this subsection, the data related to the uncertain parameters in the DA market will be presented. In the next subsection, the data related to the uncertain parameters of the RT market will be presented. Five possible scenarios are considered for each uncertain variable and they all have equal probability. Since there are three uncertain variables; each with five scenarios, a total of 125 scenarios will be generated. The uncertain parameters, their scenarios, and parameters for the DA market are presented on Table A-12 to Table A-16.

Table A-16 shows the possible scenarios for the residual prices of the RT market. It must be noted that each scenario of them will be added to each of the possible scenarios of the wind speed. This will result in 25 scenarios of the wind speed and real-time market price pairs. It must also be noted that the residual price will be added to the DA market price in order to get the RT market price.

5.1.4 RT Market Scenarios Data

The RT market simulation has to be done 24 times for the 24-hour time span. Thus, the data has to be prepared and segmented into 24 segments. In each segment/ hour, the RT price of the previous hour would be known. In addition, the renewable energy source output of that hour would be known as well with high certainty since it is not expected that the renewable energy source output will change a few minutes after bidding. This is the case because the bidding is done on hourly basis. Therefore, the data highlighted in bold on the tables reflect known/actual values while the non-bold values are estimates. The actual DA

market prices are the same as in Table A-13. Table A-17 to Table A-21 show the actual values of the uncertain parameters to be used in the RT market simulation in addition to the possible scenarios for the RT market simulation for the first hour of simulation.

During the second hour, the data will be different. This is because of a couple of factors. First, the RT market price of the previous hour has become known and it can be used in the prediction of the future hours' data. The same thing applies to the renewable energy source output. Its output for the previous hour and the current hour have become known and they can be used in the prediction model. This will make the scenarios generated different and thus the data will not be exactly the same as in the first hour. Moreover, during the simulation of the second hour for example, the first hour will be removed from the span of the study. Thus, the number of equations will be reduced with every simulated hour. Since the data will be too big to be all presented here, the data for the second and third hours will be shown and the rest of the time span will follow the same concept. This data is shown on Table A-22 to Table A-25.

5.2 DA Market Simulation

Based on the data and the model presented on the previous sections, the Day-ahead and real-time markets were simulated for 24 hours. The DA market simulation includes both the Day-ahead and real-time markets forecast. Therefore, as part of the DA market simulation, the scheduled power for the RT market as well will be obtained. However, the obtained power for the RT market will not be considered at this stage. It will be done on

hourly basis as per the RT market model. The RT market simulation includes the actual scheduled power from the DA market simulation. Therefore, the RT market simulation will have the final hourly dispatch parameters.

Table B-1 and Table B-2 show the results of the MILP for the DA market in terms of scheduled power and prices respectively. There are five scenarios considered for a 24-hour time span. It can be seen that the scheduled power is at the maximum limit of power trade with the electricity market at almost all hours. It is either at the maximum limit of power purchase which is 200 MW or the maximum limit of power sale which is 300 MW. To analyze this behavior hour by hour, Table A-14 and Table A-16 shall be considered.

It can be seen that the forecasted price of the RT market in the first two hours is higher than the forecasted DA market prices of the same hours in almost all forecasted scenarios. Therefore, it would be logical to purchase power from the DA market when the prices are lower, and then sell the extra power in the RT market when the prices are higher. When it comes to the next hour, the opposite idea happens. The forecasted prices of the RT market are lower in most of the scenarios. There are some scenarios where the RT market prices are higher, however, the residual of those prices is smaller compared to the other scenarios. Therefore, the system decides to sell power in the day-ahead market when the prices are high and tries to purchase power from the real-time market when the prices are lower. This unfortunately did not happen as all the bid prices of all scenarios are higher than the market clearing price.

Again, the same concept that was applied to the first two hours repeats for the 4th and 5th hours. The sixth hour however has a different behavior. The operator decided to sell 300 MW though there is no clear pattern that can be seen in the forecasted prices. It can be seen that there are three scenarios where the real-time market prices are higher and two scenarios where the real-time market prices are lower compared to the day-ahead market prices. The residual is also high on both the positive and negative sides. Therefore, there is no clear pattern that can be concluded at this hour and the result will be dependent on the overall optimization decision. The same analysis can be applied to the rest of the scheduling scope.

Referring to Table A-13 where the actual DA market prices are provided, the clearing power can be obtained. The actual DA market price for the first hour is 33.72. The five forecasted scenarios of the prices for the first hour are all above 33.72. Thus, all scenarios are valid. This is because the VPP operator decided to purchase 200 MW and to be able to purchase, the bid price has to be equal to or higher than the market clearing price. In this case, all the five scenarios are bidding to purchase 200 MW of power with a price higher than the clearing price. Therefore, the scenario with the highest amount of power will be the one selected. In this case, all the scenarios have the same bid power and thus, the final bid power will be 200 MW as shown on Table 5-1. On Table 5-1, some points/hours are not shown such as the third hour. This means that the scheduled power at this hour is zero. To investigate why the third hour for example has zero scheduled power, the offer and clearing prices shall be compared.

At the third hour, the actual DA market clearing price is 28.94 \$/MWh. By looking at the offered power and prices, it can be seen that the VPP wants to sell 300 MW at this hour. Therefore, the VPP has to offer with prices equal to or less than 28.94 \$/MWh. Otherwise, the VPP will fail to schedule the planned power. Unfortunately, all the offer prices are higher than the market clearing price and thus, the VPP fails to dispatch power in the day-ahead market at the third hour. Following the same analysis, the results for the rest of the planning scope can be obtained.

Table 5-1 DA market final scheduled power

Hour	Power (MW)
t1	-200
t2	-200
t4	-200
t5	-200
t9	-200
t10	-200
t12	300
t13	300
t14	300
t15	300
t16	300
t17	300
t18	300
t19	300
t20	300
t22	300
t23	300

Based on the results of the simulation of the DA market, the simulation for the RT market can be done. It should be noted that the day-ahead market scheduled power is necessary as an input to the real-time market simulation. Thus, the simulation has to be done in an order which mimics the real-life behavior as well. First, the DA market bidding/offering is done.

After that, the power mismatch can be handled in the balancing or RT market. Since the DA market bidding/offering is done for the 24 hours at once, the revenue will be calculated as the total revenue of the full day as shown on Table 5-2. The scheduled power is plotted on Figure 5-20.

Table 5-2 VPP DA market actual revenue

Revenue (\$)	110,793
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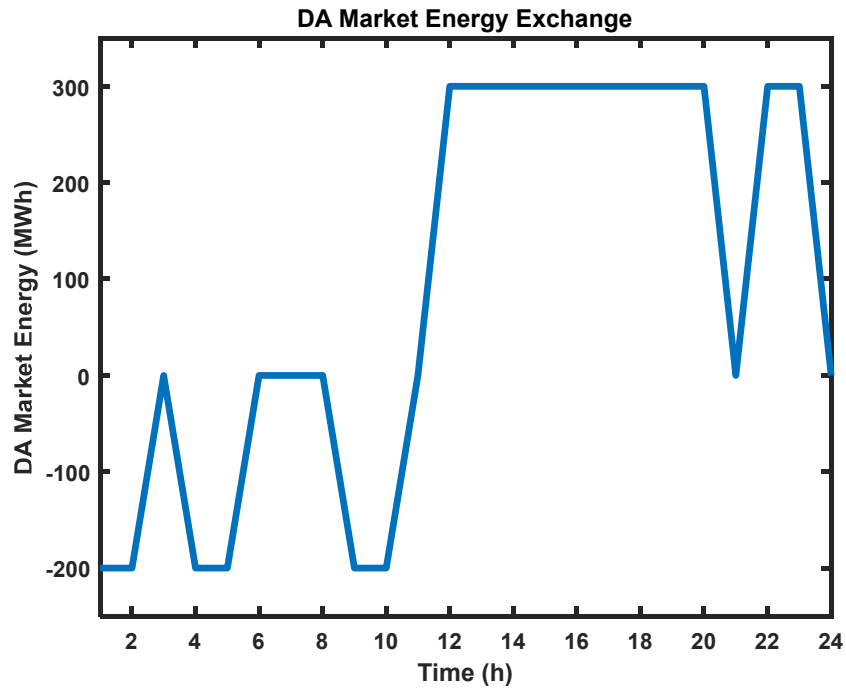


Figure 5-20 DA market final scheduled power

5.3 RT Market Simulation

In the case of the RT market simulation, there are 25 scenarios to be considered. Five scenarios for the RT market prices and five scenarios for the renewable energy source

output are considered. Thus, a total of 25 scenarios. Due to the density of the data, it will be divided into five scenarios per table. The data is provided in Table B-3 to Table B-12.

By looking at the tables above and assessing the scenarios in relation with the results of the DA market simulation, some conclusions can be drawn and the VPP behavior can be evaluated. For example, on the first, second, fourth and fifth hours in the RT market, the scheduled power is zero. Going back to the DA market, it can be seen that during those hours, the VPP has already purchased the maximum possible amount of power. Therefore, it is expected to either sell energy in the RT market or not to make any trade in the RT market. But it surely cannot purchase any extra amount of power. When it comes to the third hour, the pattern is well predicted. The VPP has traded no power in the DA market at this hour. This implies that it will need to purchase power during this hour to satisfy its minimum demand requirement especially when the output of the renewable energy source is low. During the sixth hour in the DA market, the VPP traded zero MW. So, it can either purchase until it reaches a maximum of 200 MW or it can sell in the RT market. In this case, the VPP has decided to purchase up to the maximum of the allowed amount of energy. This could be due to the fact that it could not supply its own demand at this power with the available resources. The same procedure can be used to analyze the rest of the 24 hours.

It is important to note that the RT market is an hourly market. Therefore, during the planning of the second hour, the results of the first hour would be already available which could change the decision making of the VPP. Taking the sixth hour for example: why did the VPP decide to purchase power? The answer lies in the fact that it did not purchase any

energy on the DA market at the same hour. Therefore, it is expected that the storage units are already completely discharged and that the renewable energy source is giving a small amount of power. Thus, the network is relying completely on the supply from the conventional power source. This implies that the VPP will need to purchase extra power from the grid. Therefore, thorough analysis shall be done in order to understand the behavior of the system. On the next tables, where the battery charging status is presented, it may confirm the current analysis of the results.

Now that the price and power curves are available, the RT market clearing price is needed in order to obtain the actual dispatched power. The actual RT market prices were shown previously on Table A-18. On the third hour, the forecasted prices of the RT market vary generally between around 33 \$/MWh to around 36 \$/MWh. The actual market clearing price is 30.96 \$/MWh. Therefore, it is expected that the deal will be executed since the offer price falls within the scenarios range. Figure 5-21 shows a plot of the RT market scheduled power.

Table 5-3 RT market final scheduled power

Hour	Power (MW)
t3	-200
t6	-200
t7	-200
t8	-200
t11	-200
t13	-421.11
t14	-500
t15	-500
t16	-500
t17	-500
t19	-500

Hour	Power (MW)
t21	-200
t22	-500

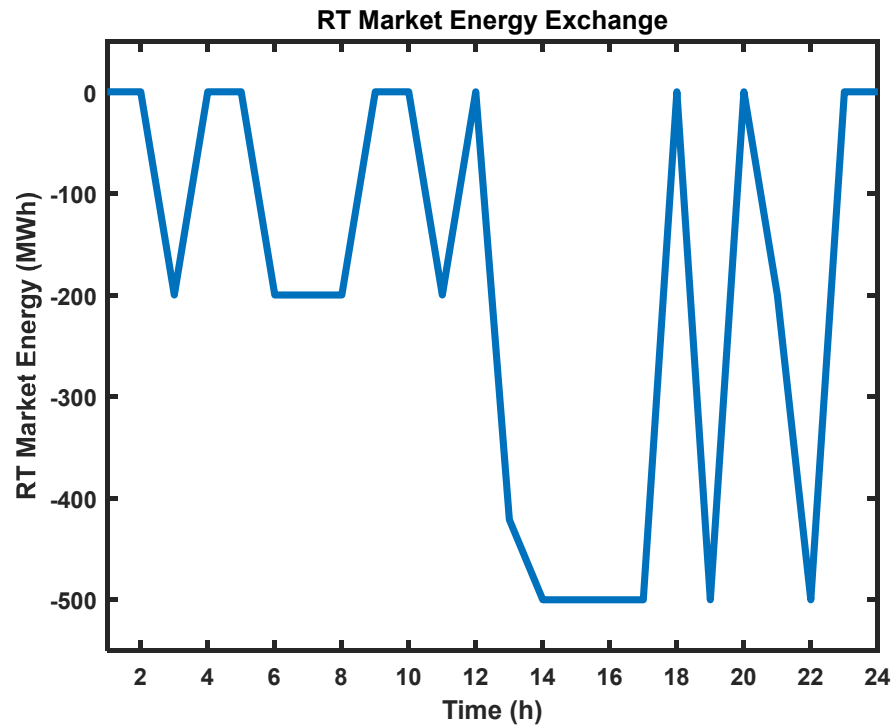


Figure 5-21 RT market final scheduled power

On Table 5-3, the final scheduled power in the RT market is decided. As per the analysis carried above, all the results are acceptable in terms of scheduling, dispatching, bidding and offering. However, at 4 hours of the day, there is an issue due to the difference between scheduling and dispatching. On Table 5-3, some hours are not shown and that is because the power at those hours is zero. This is because the bid/offer price did not match that of the market clearing price. Therefore, the dispatched power will be as on Table 5-3. This has caused an issue on the 12th, 18th, 20th and 23rd hours. The issue was caused because the VPP has made a plan/schedule in the Day-ahead and real-time markets based on forecasted data. This forecasted data did not match the actual one very well which caused the VPP to

be unable to participate in the markets at some hours. This is normal only if the VPP can satisfy its own demand during the hours when it failed to participate in the markets. On those aforementioned four hours, the issue that happened is that the virtual power plant could not win the bid in the RT market and was unable to supply its own demands.

The VPP in this case has to solve the issue of power mismatch through any other source as it cannot any longer handle it through the DA or RT markets. This will probably as well cost higher amount of money. In other words, the MILP is not feasible at the 12th, 18th, 20th and 23rd hours. Based on the dispatched power as shown above, the revenue of the VPP can be obtained as shown on Table 5-4. This revenue is related to the RT market only. It can be added to that of the DA market in order to obtain the overall revenue, profit, and dispatch parameters.

Table 5-4 VPP RT market actual revenue

Hour	Revenue (\$)
t3	-6,042
t6	-6,414
t7	-7,926
t8	-7,102
t11	-7,202
t13	-20,107.8
t14	-20,260
t15	-17,510
t16	-17,460
t17	-17,995
t19	-18,820
t21	-7,546
t22	-17,185

Table 5-5 Conventional generator status

Hour	Conventional Generator Status (1=up)
t1	1
t2	1
t3	1
t4	1
t5	1
t6	1
t7	1
t8	1
t9	1
t10	1
t11	1
t12	1
t13	1
t14	1
t15	1
t16	1
t17	1
t18	1
t19	1
t20	1
t21	1
t22	1
t23	1
t24	1

Table 5-6 Storage charge and discharge

Hour	Storage Discharge (MWh)	Storage Charge (MWh)	State of Charge (MWh)
t1	100.00	0.00	88.89
t2	69.15	0.00	12.06
t3	10	0.00	0.95
t4	0.853	0.00	0.00
t5	0.00	0.00	0.00

It can be seen from Table 5-5 and Table 5-6 that the conventional generator was running during the whole scheduling scope. Also, it can be seen that by the 5th hour, the storage unit has become completely discharged. This agrees with the previous analysis for the 12th,

18th, 20th and 23rd hours. By the 12th hour for example, the storage unit was completely discharged and it is expected also that the conventional generator would be running at the maximum possible output while the renewable energy source output is expected to be low.

Table B-13 to Table B-17 show the demand at each bus. Each demand is composed of four loads. Table 5-7 shows the power of all the sources in the VPP in addition to the total demand of the VPP at each hour. The total demand is the summation of all demands aforementioned in the previous tables. This table gives clear understanding on whether the VPP will need to purchase or sell energy at each hour or not. It can be seen that that the demand is much higher than the generation at almost all hours and thus the VPP will need to purchase energy overall. Only at the last hour of the planning scope it can be noticed that the VPP has equal power generation and demand.

Table 5-7 Power Exchange

	Conventional Generator (MW)	Renewable Source (MW)	Storage Energy (MW)	Total Generation (MW)	Demand (MW)
t1	170.00	1.83	100.00	271.83	471.83
t2	230.00	0.85	69.15	300.00	500.00
t3	290.00		10.00	300.00	500.00
t4	294.00	0.69	0.85	295.54	495.54
t5	294.00			294.00	494.00
t6	294.00			294.00	494.00
t7	294.00			294.00	494.00
t8	294.00	1.25		295.25	495.25
t9	294.00	0.36		294.36	494.36
t10	294.00			294.00	494.00
t11	294.00	5.71		299.71	499.71
t12	294.00	3.62		297.62	497.62
t13	294.00	5.65		299.65	420.75
t14	294.00	8.52		302.52	502.52

	Conventional Generator (MW)	Renewable Source (MW)	Storage Energy (MW)	Total Generati on (MW)	Demand (MW)
t15	294.00	8.84		302.84	502.84
t16	294.00	7.01		301.01	501.01
t17	294.00	12.51		306.51	506.51
t18	294.00	14.74		308.74	508.74
t19	294.00	9.64		303.64	503.64
t20	294.00	6.67		300.67	500.67
t21	294.00	3.11		297.11	497.11
t22	294.00	10.03		304.03	504.03
t23	294.00	11.10		305.10	505.10
t24	294.00	11.26		305.26	305.26

Table 5-8 Day-ahead and real-time markets final scheduled power

Hour	DA Power (MW)	RT Power (MW)	Total Power (MW)
t1	-200	0	-200
t2	-200	0	-200
t3	0	-200	-200
t4	-200	0	-200
t5	-200	0	-200
t6	0	-200	-200
t7	0	-200	-200
t8	0	-200	-200
t9	-200	0	-200
t10	-200	0	-200
t11	0	-200	-200
t12	300	0	300
t13	300	-421.11	-121.11
t14	300	-500	-200
t15	300	-500	-200
t16	300	-500	-200
t17	300	-500	-200
t18	300	0	300
t19	300	-500	-200
t20	300	0	300
t21	0	-200	-200

Hour	DA Power (MW)	RT Power (MW)	Total Power (MW)
t22	300	-500	-200
t23	300	0	300
t24	0	0	0

Lastly, Table 5-8 confirms all the previously made analysis. Looking at the total power/energy exchange we can find that the VPP will almost always need to purchase power from the grid. The only exclusion is the last hour which is balanced. The issue now becomes very clear for the 12th, 18th, 20th and 23rd hours. The reason why an issue happened is because the VPP decided to sell energy in the day-ahead market assuming it will be able to buy it again in the RT market to make profit. Unfortunately, due to the failure of meeting the market clearing price at the RT market, the scheduling did not go as planned and the VPP failed to supply its demand at those hours.

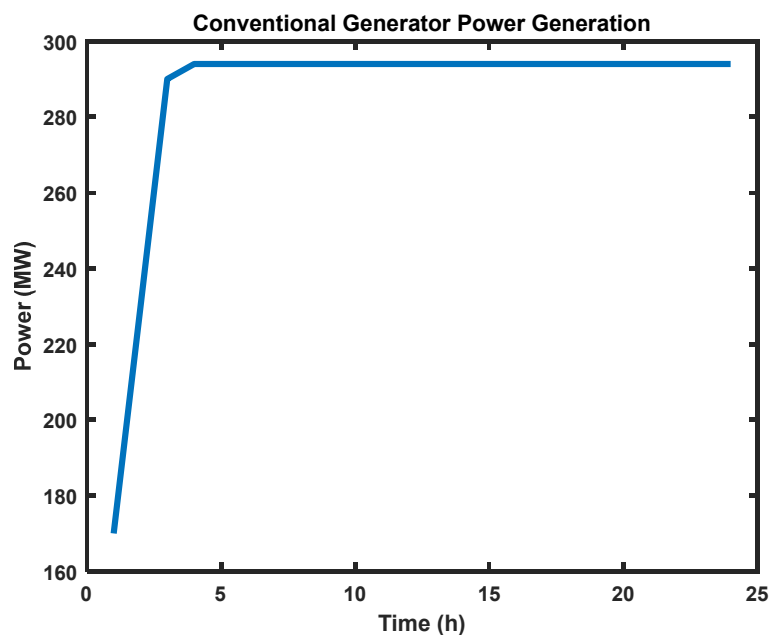


Figure 5-22 Conventional generator power generation

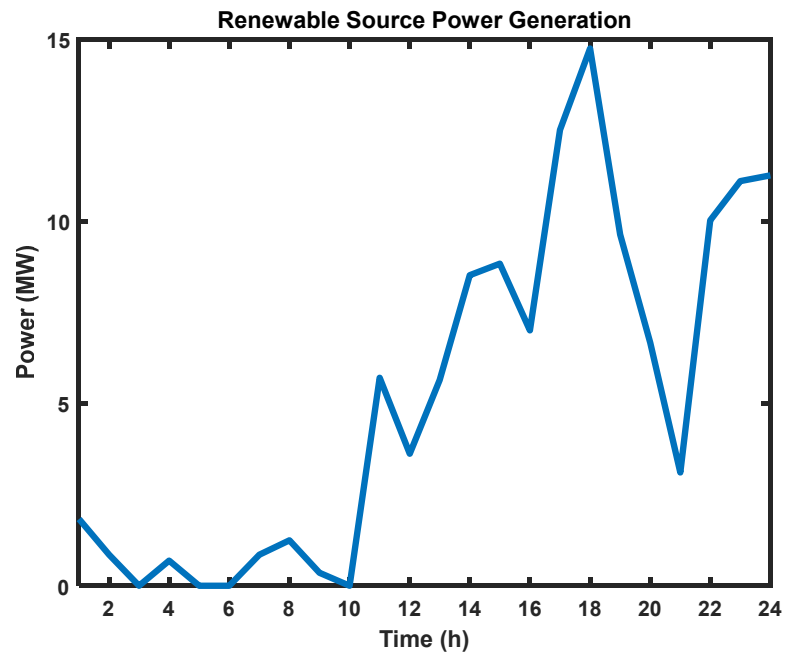


Figure 5-23 Renewable source power generation

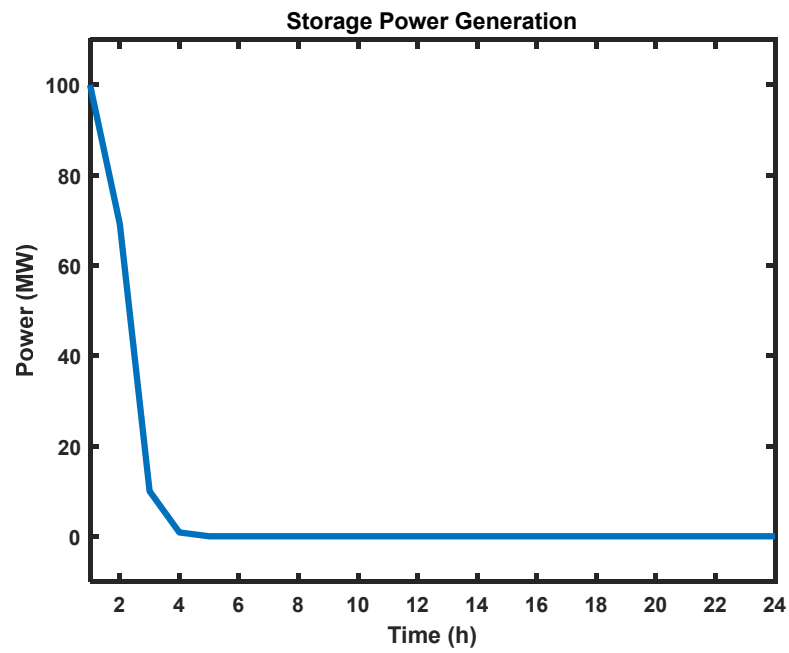


Figure 5-24 Storage power generation

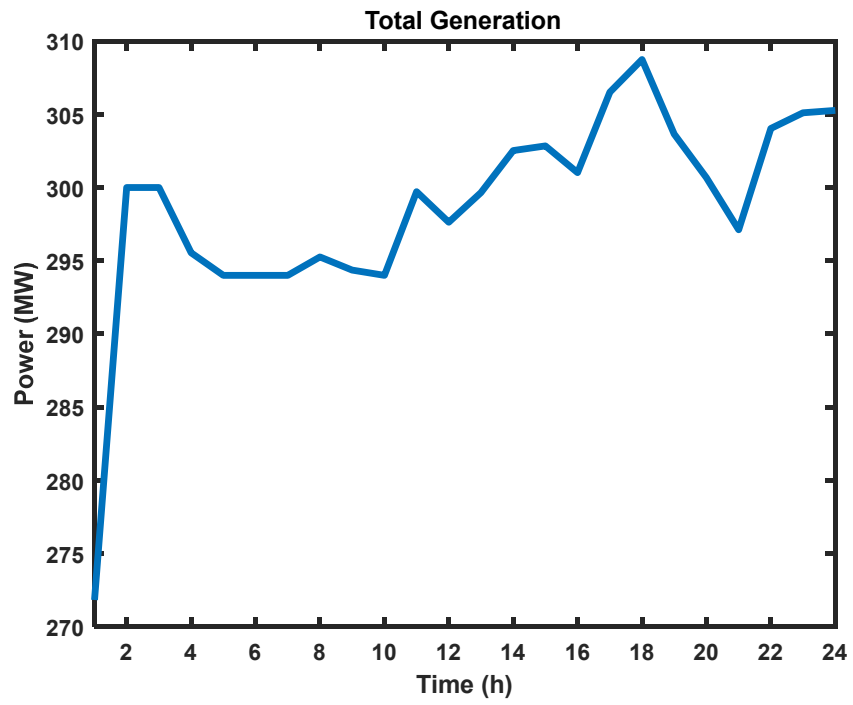


Figure 5-25 Total power generation

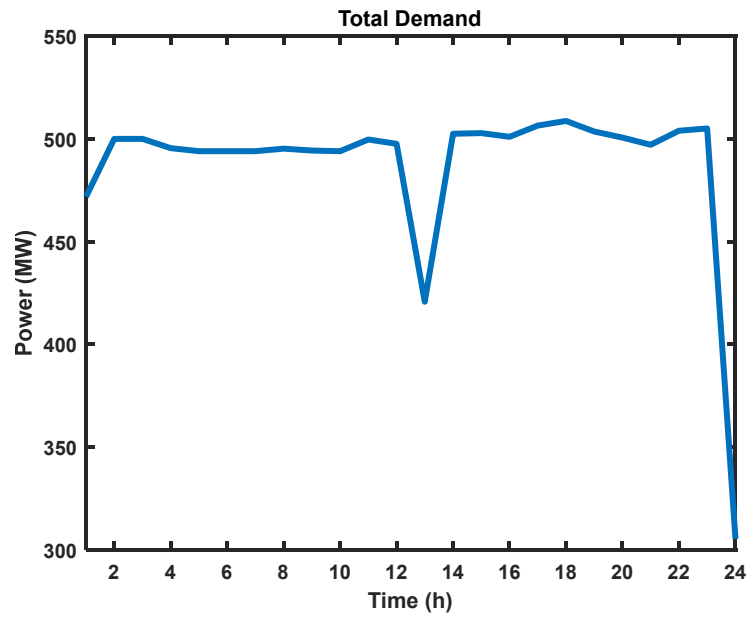


Figure 5-26 Total demand

Figure 5-22 to Figure 5-24 show the power generation of the conventional generator, renewable energy source and the storage unit respectively. Figure 5-25 shows the total power generated by the VPP while Figure 5-26 shows the total demand required by the VPP. Figure 5-27 presents the cumulative power generated, traded with the market and the demand. First, the conventional generator power is plotted, then the renewable energy source power is added to the conventional one and plotted. Next, the storage unit generated power is added to the previous two and plotted. Lastly, the power traded with the market is added to them and plotted. The overall plot matches the demand plot except for 4 points where the VPP plan did not converge as mentioned earlier. It can be seen that at some points, the power generated is negative. This means that the power sold to the network is more than the total power generated by the VPP which is a possible consequence of the non-convergence of the model at this hour.

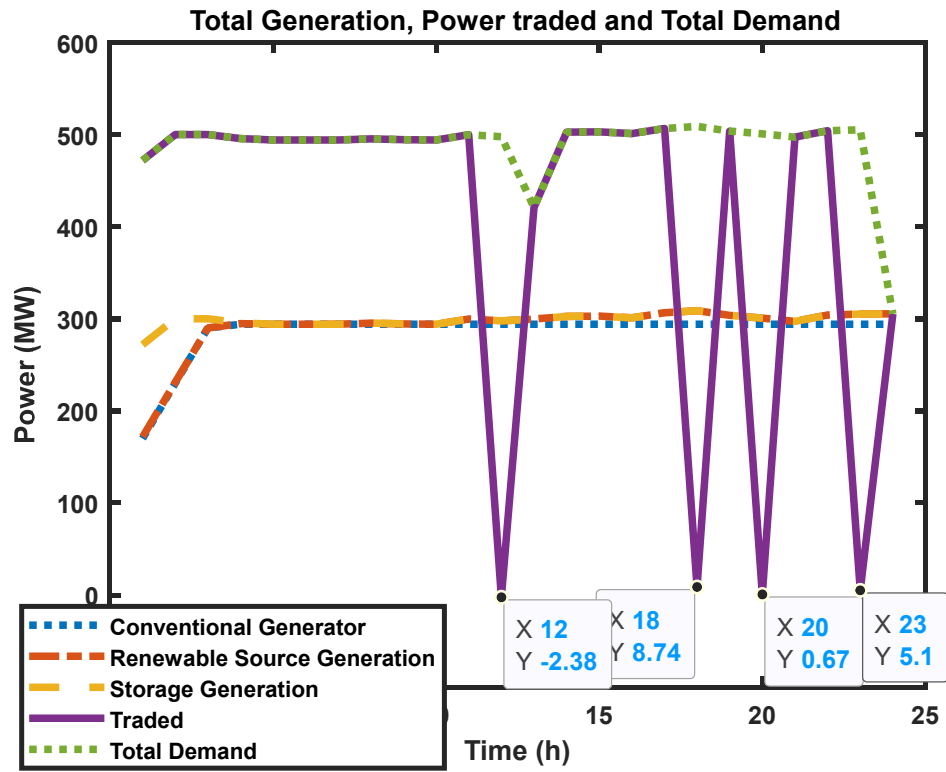


Figure 5-27 Total generation, power traded and demand

Table 5-9 Hourly net profit without DA market revenue

Hour	Profit (utility – generator cost) (\$)	RT Revenue (\$)	Net profit (\$)
h1	25,277.52	0.00	25,277.52
h2	25,901.50	0.00	25,901.50
h3	23,184.50	-6,042.00	17,142.50
h4	22,748.53	0.00	22,748.53
h5	22,661.90	0.00	22,661.90
h6	22,661.90	-6,414.00	16,247.90
h7	22,661.90	-7,926.00	14,735.90
h8	22,598.08	-7,102.00	15,496.08
h9	17,610.61	0.00	17,610.61
h10	17,707.37	0.00	17,707.37
h11	17,960.37	-7,202.00	10,758.37
h12	17,804.58	0.00	17,804.58
h13	14,111.75	-20,107.76	-5,996.01
h14	18,098.12	-20,260.00	-2,161.88
h15	18,070.21	-17,510.00	560.21
h16	17,967.63	-17,460.00	507.63
h17	21,723.10	-17,995.00	3,728.10
h18	21,847.31	0.00	21,847.31
h19	21,566.64	-18,820.00	2,746.64
h20	21,403.33	0.00	21,403.33
h21	21,207.61	-7,546.00	13,661.61
h22	21,621.39	-17,185.00	4,436.39
h23	21,679.47	0.00	21,679.47
h24	10,230.25	0.00	10,230.25

Table 5-9 shows the utility profit which is the profit the VPP will make by supplying its own demand. In addition to this profit, there is a revenue made by selling to or purchasing from the electricity market. Adding those together will result in the net profit. However, the revenue of the VPP overall is still not yet finalized as it must be added to the revenue of the DA market. The DA market revenue was not added to the last table since it is calculated for the 24 hours and not on hourly basis. Therefore, Table 5-10 shows the overall net profit which is the summation of the hourly profit shown on Table 5-9 in addition to

the DA market revenue. By this, the simulation of the two markets is done and the final net profit is calculated.

Table 5-10 DA and RT markets net profit

Utility and RT Profit (\$)	DA Market Net Profit (\$)	Net profit (\$)
316,735.82	110,793	427,528.82

5.4 Weighing Factor Effect

In this section, the weighing factor, beta, of the CVaR model will be varied from 0 to 2.0 to see its effect on the worst-case scenario consideration. The effect of varying beta from 0 to 2.0 is going to be presented through the figures of the DA market energy exchange, RT market energy exchange, total demand, total generation, and the total profit.

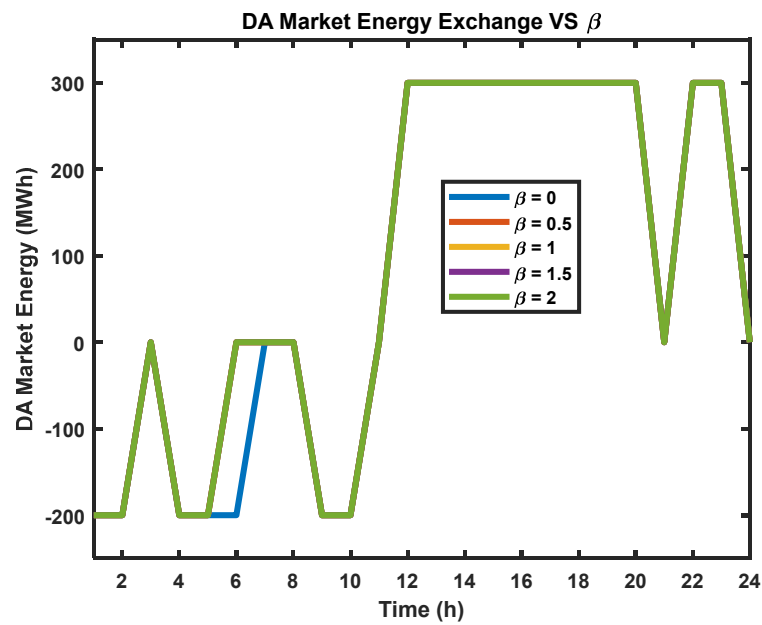


Figure 5-28 DA market energy exchange VS beta

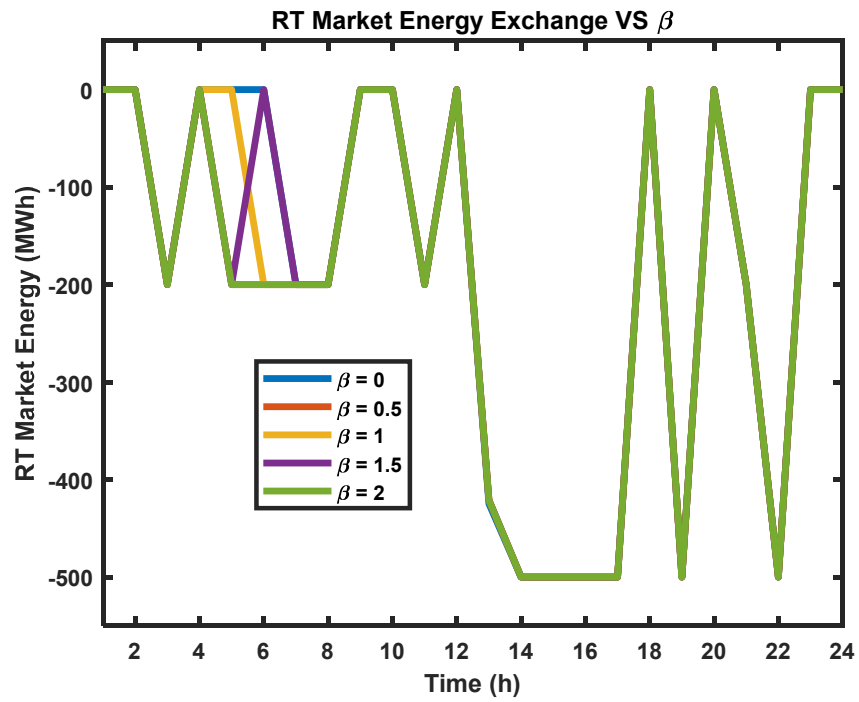


Figure 5-29 RT market energy exchange VS beta

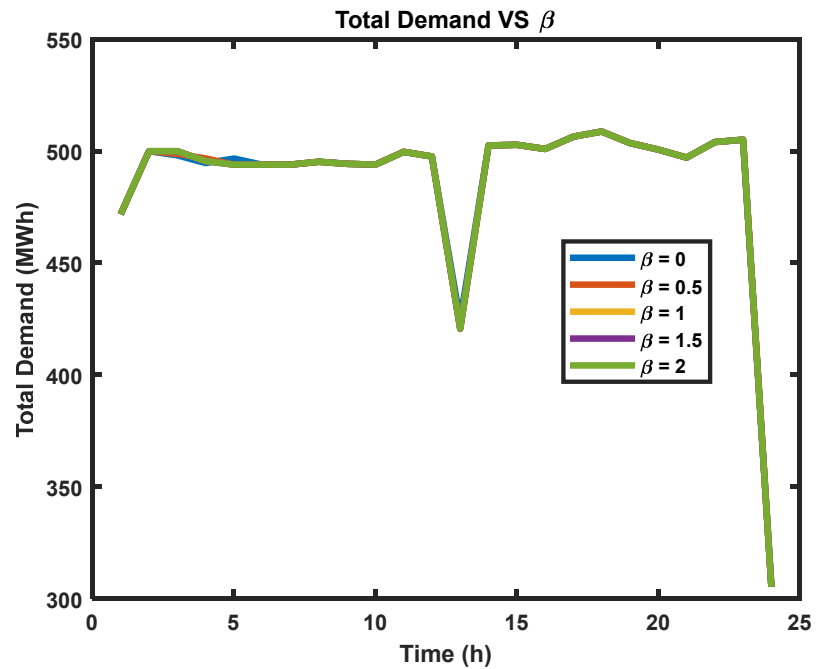


Figure 5-30 Total demand VS beta

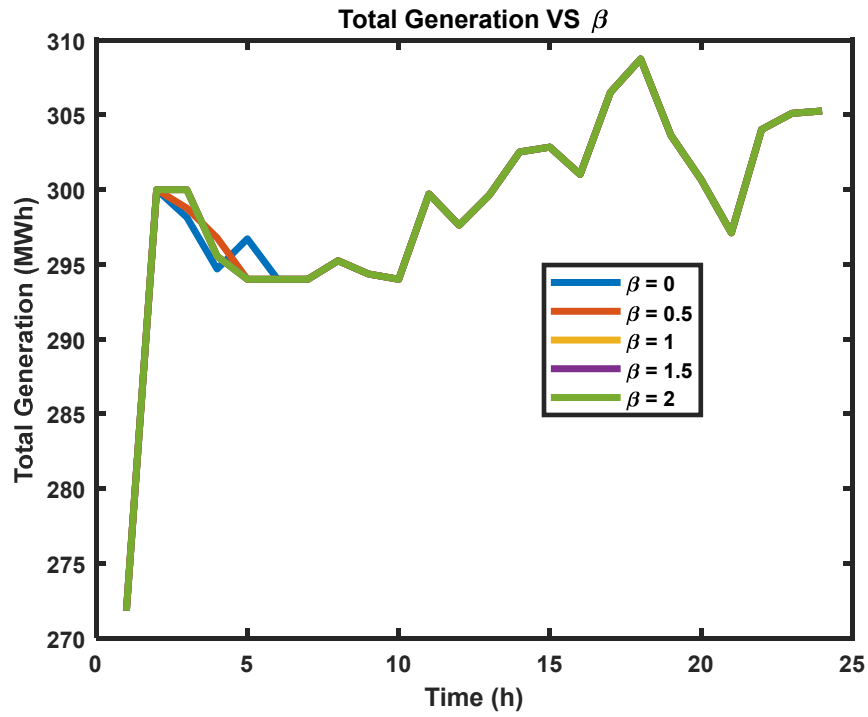


Figure 5-31 Total generation VS beta

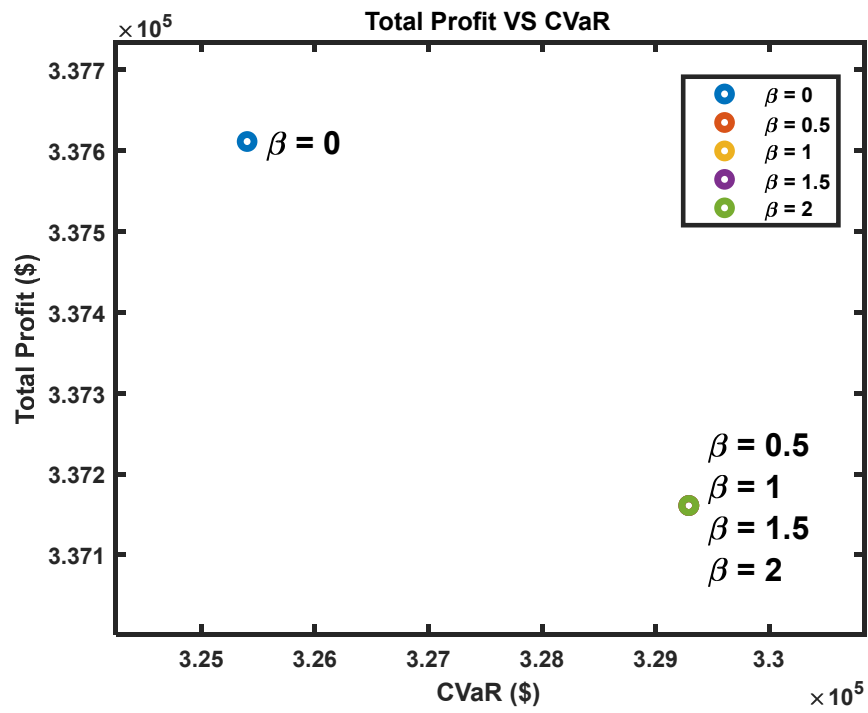


Figure 5-32 Total profit VS CVaR

It can be seen that the demand and generation are almost exactly the same for all values of beta with slight variation at the early hours of the day. On the other hand, there is some difference at the 6th hour in the Day-ahead and real-time market energy exchange. Those slight differences are eventually translated as profit or loss. It is presumably expected that the overall profit of the two markets shall decrease with the increase of the risk weighing factor, beta. This is exactly what is shown on Figure 5-32 where the scenario where beta equals zero has the highest profit. Also, the scenario where beta is the highest results in the lowest profit.

5.5 Models Comparison

In the section where the values of beta are compared, the case of beta equals zero is considered. This is in fact the stochastic model without consideration of risk. Therefore, there are now two available models to compare. The main model presented in this dissertation with beta equals one and the model that does not consider risk where beta is equal to zero. Another model that is useful to add for the comparison purposes is the deterministic model. By comparing those three models, the dissertation would have covered all the non-robust optimization MILP models of the VPP in the Day-ahead and real-time markets.

It can be seen from the comparison shown on tables Table B-18 to Table B-22 that the deterministic model has failed at a higher number of hours. The hours of failure of power balance are marked in red on the tables. The deterministic model has succeeded to

participate at all hours of the DA market and failed to participate at many hours of the RT market which has resulted in the power imbalance with that high rate. The tables of demand and generation are relatively close at all hours for all models. As expected, it can be seen on Table B-22 that the deterministic model has higher profit from both the Day-ahead and real-time markets compared to the other models and thus higher overall profit. The other two models have close values in terms of profit with the model that considers risk being the lowest profit maker. Table B-18 to Table B-22 are presented into figure form for an easier visual understanding of the results as per Figure 5-33 to Figure 5-37.

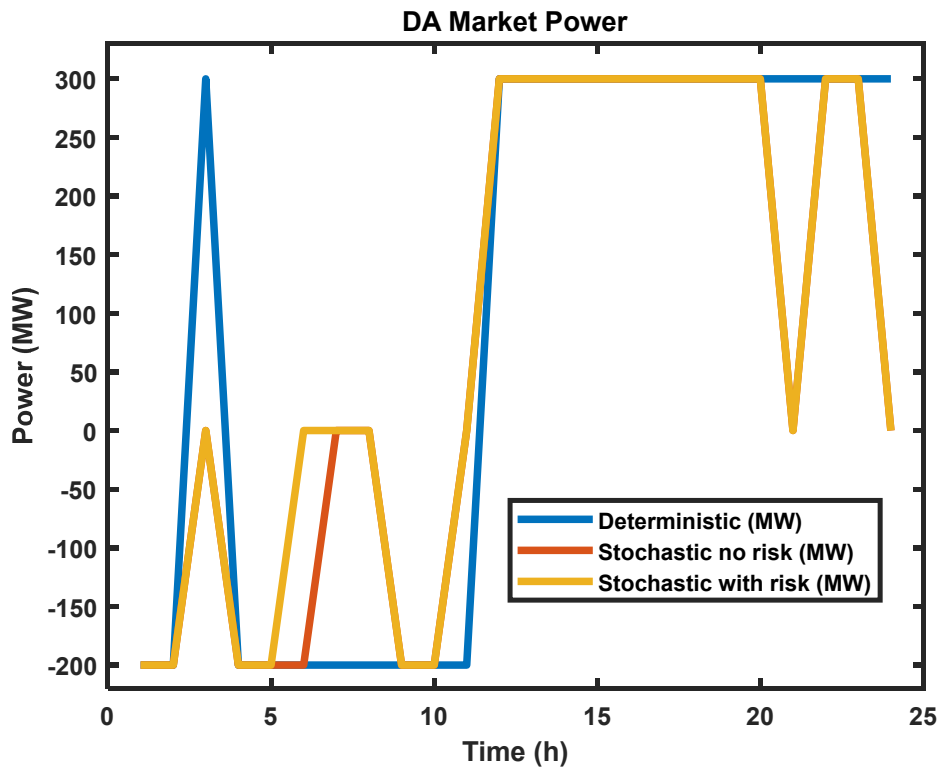


Figure 5-33 DA market power

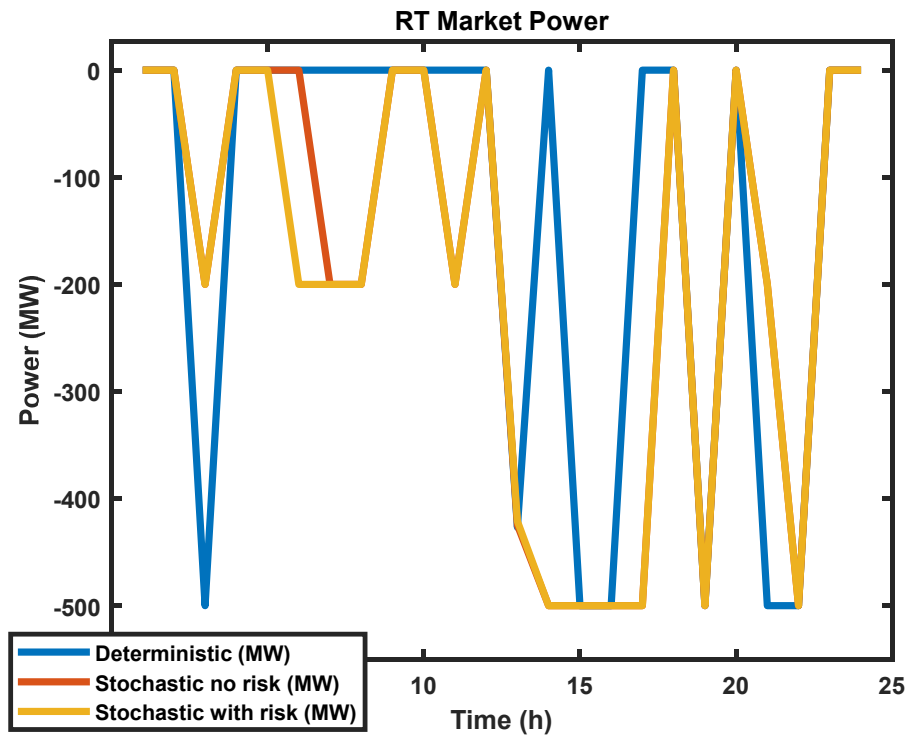


Figure 5-34 RT market power

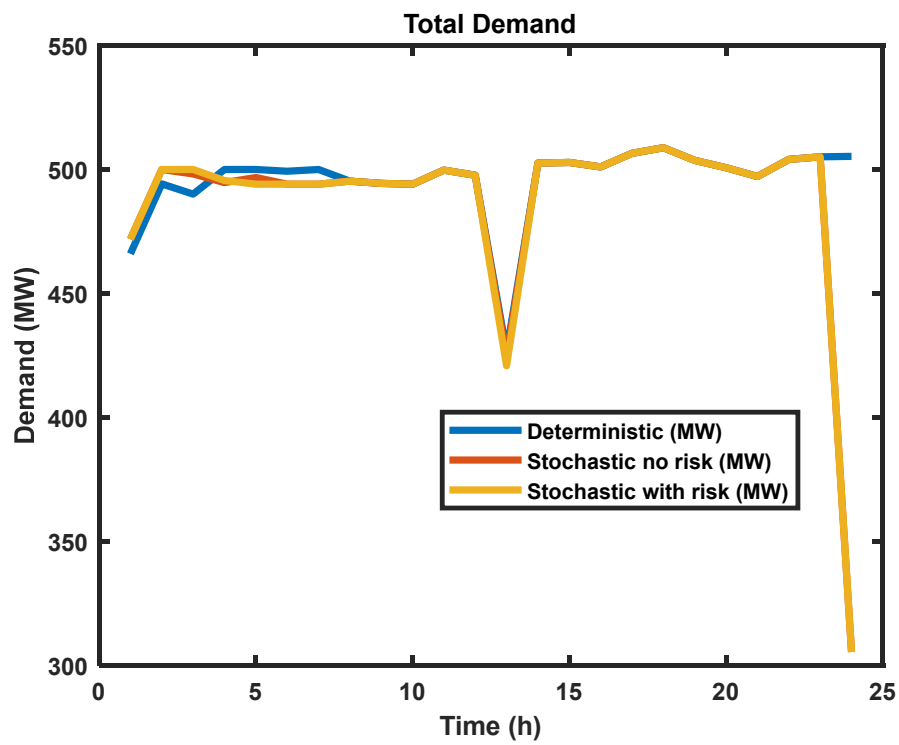


Figure 5-35 Total demand

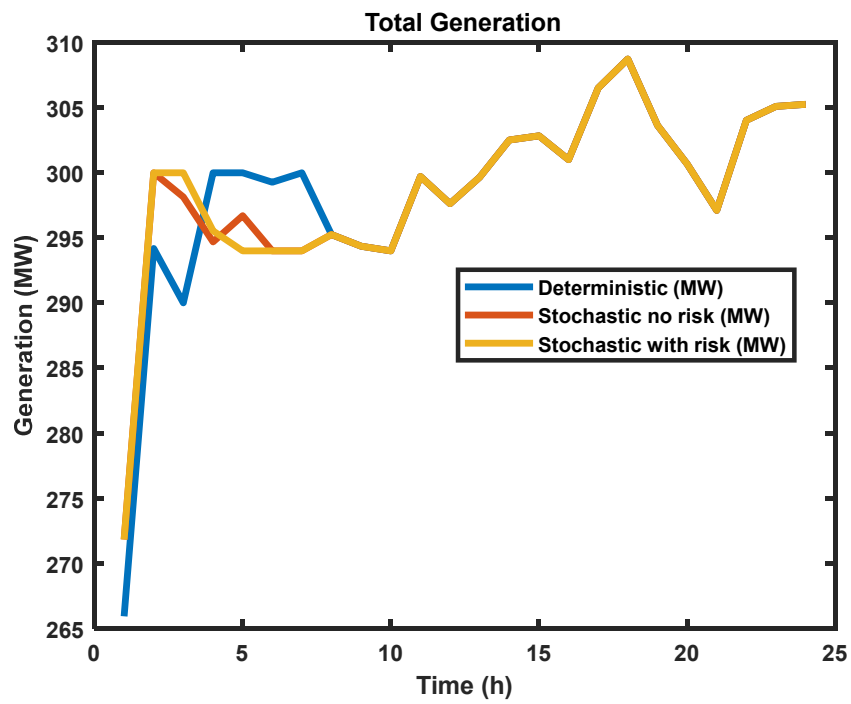


Figure 5-36 Total generation

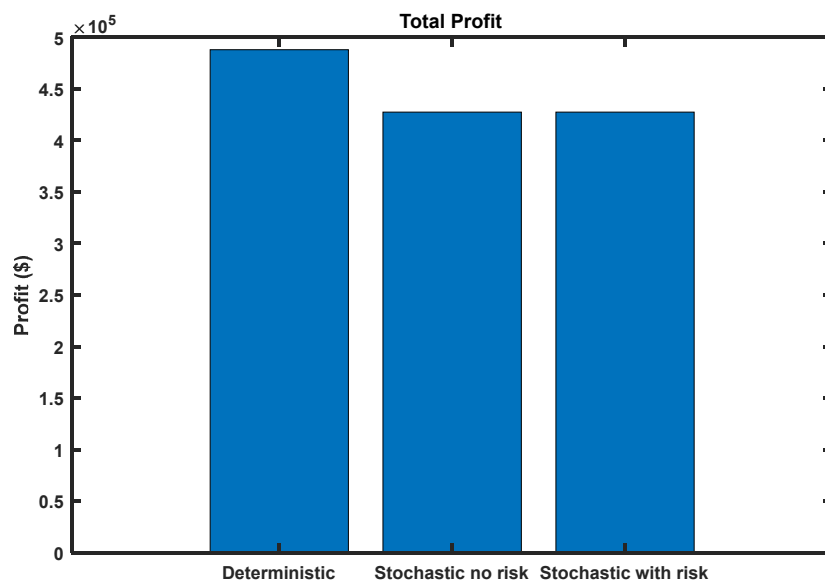


Figure 5-37 Profit

It can be concluded that the deterministic model fails to make the right predictions and thus fails to balance the power. Therefore, a model with higher historical data dependence and multiple possibilities considerations is required. The deterministic model also gives very optimistic profit expectation which is not realistic due to the fact that loss of power balance may and most probably will cost the VPP owner a lot more than the extra expected profit.

5.6 ARIMA VS Sequential ARIMA

In literature, many research papers consider a short prediction scope, usually less than 10 hours when it comes to using the ARIMA model or even other models that predict future data points. This is especially the case when it comes to the wind power data for example. Wind power is hard to predict using ARIMA for a big number of future hours. A good suggestion to overcome this issue is to use ARIMAX where both the wind speed and wind power data are used in order to predict future wind power data points. Nevertheless, a prediction in general becomes less accurate if a big number of forecast hours are considered.

In literature, an ARIMA model is usually developed then used to predict the future data points in the study horizon of the research. What is recommended in this dissertation is to make use of the fact that the RT market is an hourly market unlike the DA market. This means that for the DA market, a similar style to literature is used where the full time-horizon of the study, 24 hours here, is predicted at once. However, for the RT market, it is proposed to use sequential/ hour-by-hour forecasting instead. This means that for the first

hour of the time horizon, the 24 hours scope is predicted. Before the second hour, the first hour data has become known and thus, it can be included in the historical data before predicting the second hour. This pattern is followed until the full time-horizon is covered.

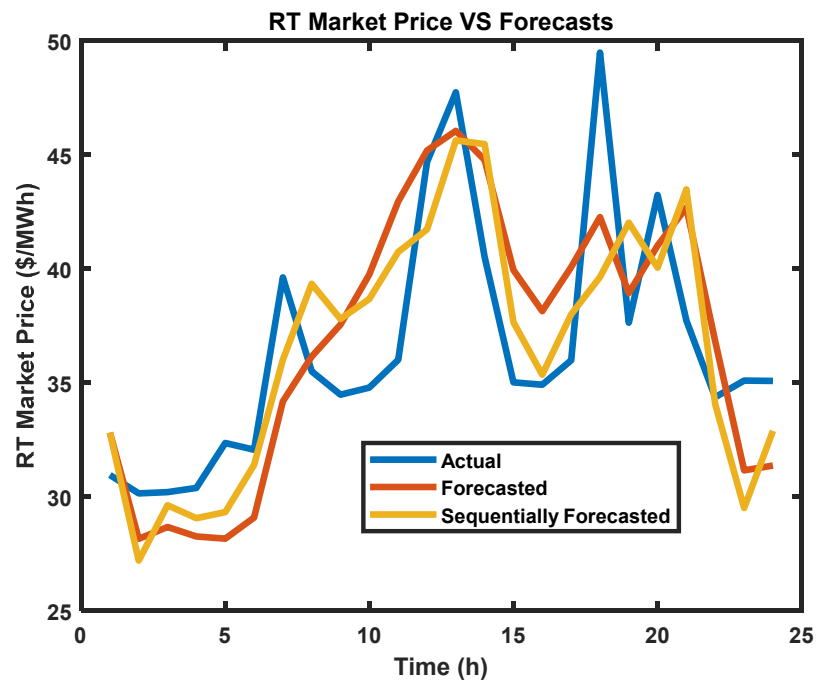


Figure 5-38 RT market price VS forecasts

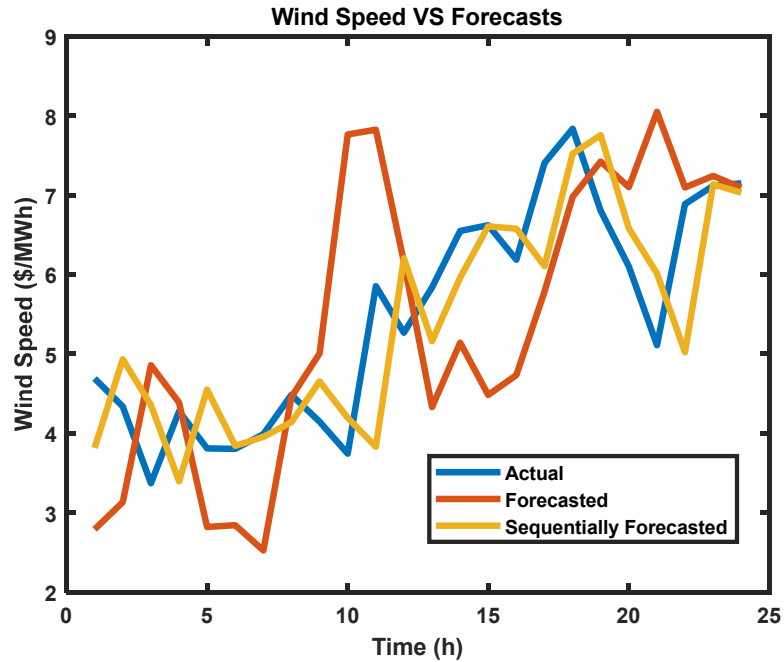


Figure 5-39 Wind speed VS forecasts

On Figure 5-38, the actual RT market prices for the 24 hours of the study scope are presented. Along with that, the forecast of the 24 hours is shown on the same figure where the forecast of all the 24 hours is made at once. Additionally, the proposed sequential forecasting is presented on the same figure. It can be seen that both forecasting methods are relatively good with no major difference. Nonetheless, the case is different with the wind speed data shown on Figure 5-39. It can be seen that the proposed model of sequential forecast is much closer to the actual data than the ordinary method. Table 5-11 shows the root mean square error (RMSE) which confirms the explanation above.

Table 5-11 RMSE of ARIMA and Sequential ARIMA

	Ordinary Forecast Model	Proposed Sequential Forecast Model
RMSE of RT Market Prices	3.79	3.79
RMSE of Wind Speed	1.55	0.846

5.7 Generator Variable Cost Models Comparison

Getting back to the main model considered in this research, the stochastic model considering risk with beta equals one, two sub-models will be evaluated. In this research, it is proposed to use a variable generator cost model into the MILP for higher accuracy. This part is usually simplified in literature by taking the variable generation cost as a fixed value multiplied by the generator's output power. A good example of this simplification is the case presented in [170]. A linearization method is used in this research to convert the piecewise variable generation cost model into a LP model. This is expected to result in higher accuracy which will be presented through the comparison of the system having the simplified variable generation cost model to the system having the proposed variable generation cost model.

After running the two simulations, the data is almost identical in terms of DA market power, RT market power, demand, and generation. Thus, presenting this almost-identical data will be avoided as it has already been presented earlier. The major difference is in the revenue achieved from the utility.

Table 5-12 Proposed VS simplified generator variable cost model

Hour	Proposed Model Utility (\$)	Simplified Model Utility (\$)	Difference (\$)	Percent Difference (%)
1	25,277.52	25,035.07	242.45	0.96%
2	25,901.50	25,660.50	241.00	0.93%
3	23,184.50	23,096.30	88.20	0.38%
4	22,748.53	22,738.68	9.85	0.04%
5	22,661.90	22,699.90	-38.00	-0.17%
6	22,661.90	22,699.90	-38.00	-0.17%
7	22,661.90	22,851.95	-190.05	-0.84%
8	22,598.08	22,636.08	-38.00	-0.17%
9	17,610.61	17,648.61	-38.00	-0.22%
10	17,707.37	17,748.90	-41.53	-0.23%
11	17,960.37	17,959.71	0.66	0.00%
12	17,804.58	17,880.61	-76.03	-0.43%
13	14,111.75	14,112.75	-1.00	-0.01%
14	18,098.12	18,147.22	-49.10	-0.27%
15	18,070.21	18,082.61	-12.40	-0.07%
16	17,967.63	18,005.63	-38.00	-0.21%
17	21,723.10	21,761.10	-38.00	-0.17%
18	21,847.31	21,885.31	-38.00	-0.17%
19	21,566.64	21,604.64	-38.00	-0.18%
20	21,403.33	21,441.33	-38.00	-0.18%
21	21,207.61	21,245.61	-38.00	-0.18%
22	21,621.39	21,659.39	-38.00	-0.18%
23	21,679.47	21,717.47	-38.00	-0.18%
24	10,230.25	10,268.25	-38.00	-0.37%

It can be seen that the simplified model which is a linear approximation has an error of around $\pm 0.5\%$ per hour due to the simplification used. This is happening because the simplified model uses a fixed average slope for the variable generation cost and multiplies it by the amount of power generated. This will result into a linear relationship between the variable generation cost and the power generated. The proposed model is however piecewise model which is more realistic, more accurate, and also results into higher

expected profit. In some papers, a more accurate model is used such as the model used in [76], [171] and [181]. The model in those references uses constraints to introduce the piecewise model of the generator variable cost which gives exactly the same results as the proposed model. Thus, the model in [76], [171] and [181] is equivalent to the proposed model in terms of accuracy. Nonetheless, as per [182], the SOS2 model is only computationally faster. The SOS2 model and the constraints model were tested to assess the computational speed of each model.

As shown on Table 5-13, it has been found that the SOS2 model consumed 50% more time for one iteration of simulation compared to the constraints model when it executed the same task. This could be due to the limited number of blocks used to represent the variable generation cost. The claim made in [182] could be correct for cases where the piecewise curve has a bigger number of blocks. It is however proven to be slower in this case.

Table 5-13 SOS2 Vs Constraints models speed comparison

Model	Time (seconds)
SOS2 Model	120
Constraints Model	80

CHAPTER 6

Energy Pool Based VPP

6.1 VPP Model Expansion

It can be seen from the previous sections that the failure rate of participation into the RT market was high which requires a more sophisticated methodology in order to reduce this high failure rate. Additionally, the loads though being flexible, are general loads. It is important to include specific loads into the VPP for a more advanced modelling and deeper analysis of more realistic cases. It is proposed to include a water desalination unit (WDU) as a specific load type due to its importance especially in countries that rely heavily onto water desalination such as Saudi Arabia. Water desalination units have a huge infrastructure and they can serve as virtual storage units. These reasons make it very essential to consider such type of load and to consider its way of interaction with the electrical network.

In order to reduce the failure rate of participation into the market, it is proposed to add reliability as another objective in this multi-objective optimization model. Therefore, the model will try to maximize profit, reduce cost, and increase the reliability of the VPP in terms of success rate of participation into the electricity markets. Based on these

amendments to the proposed model a comprehensive multi-objective VPP would be ready for further analysis and thus for the construction of a VPP cluster.

6.2 Energy Pool Introduction

The idea of energy pool (EP) is used in literature with microgrids mainly. An energy pool is a common source of power between multiple microgrids. The idea of combining multiple microgrids with a common energy pool is called microgrid clustering. Therefore, the structure of a microgrid cluster has a central energy pool which is common between multiple microgrids that can be AC microgrids or DC microgrids. The energy pool could be a set of batteries that are exchanging power with the microgrids through a power exchange unit (PEU).

The microgrid cluster mainly aims to have power balance in all the interconnected microgrids through some control strategies onto the PEU, [175]. The control can be through the assessment of the voltage of the DC bus for DC microgrids and through monitoring the frequency of the AC bus of AC microgrids. Applying the interconnection between the EP and the MC can be a permanent structure and can be based on some criteria. For example, the MC may connect to the EP in case of a blackout that results into the MC working on an islanded mode, [176]. The structure of the microgrid clusters can be concerned with DC microgrids only, [177]-[179], and can be concerned with mixed AC and DC microgrids, [175], and can even be concerned with PV based microgrids only, [180]. The structure of

the MC specifies the range of control schemes that can be used in order to achieve power stability.

6.3 Developed VPP Cluster

The idea of connecting an energy pool to a VPP has not been assessed in the literature before and this is due to the fact that a VPP's main objectives are to maximize profit through participation into the electricity market and to ensure the reliability of this participation into the markets. Therefore, it is an economic point of view while an energy pool is not used for the purpose of profit making but rather for the purpose of power balance. In this research, it is proposed to develop a structure that combines the EP with the VPP for the power balance purposes along with profit maximization. Therefore, this is a new development that has not been introduced into the literature before. The next flowchart explains how the interaction between the different VPPs and the EP will be like.

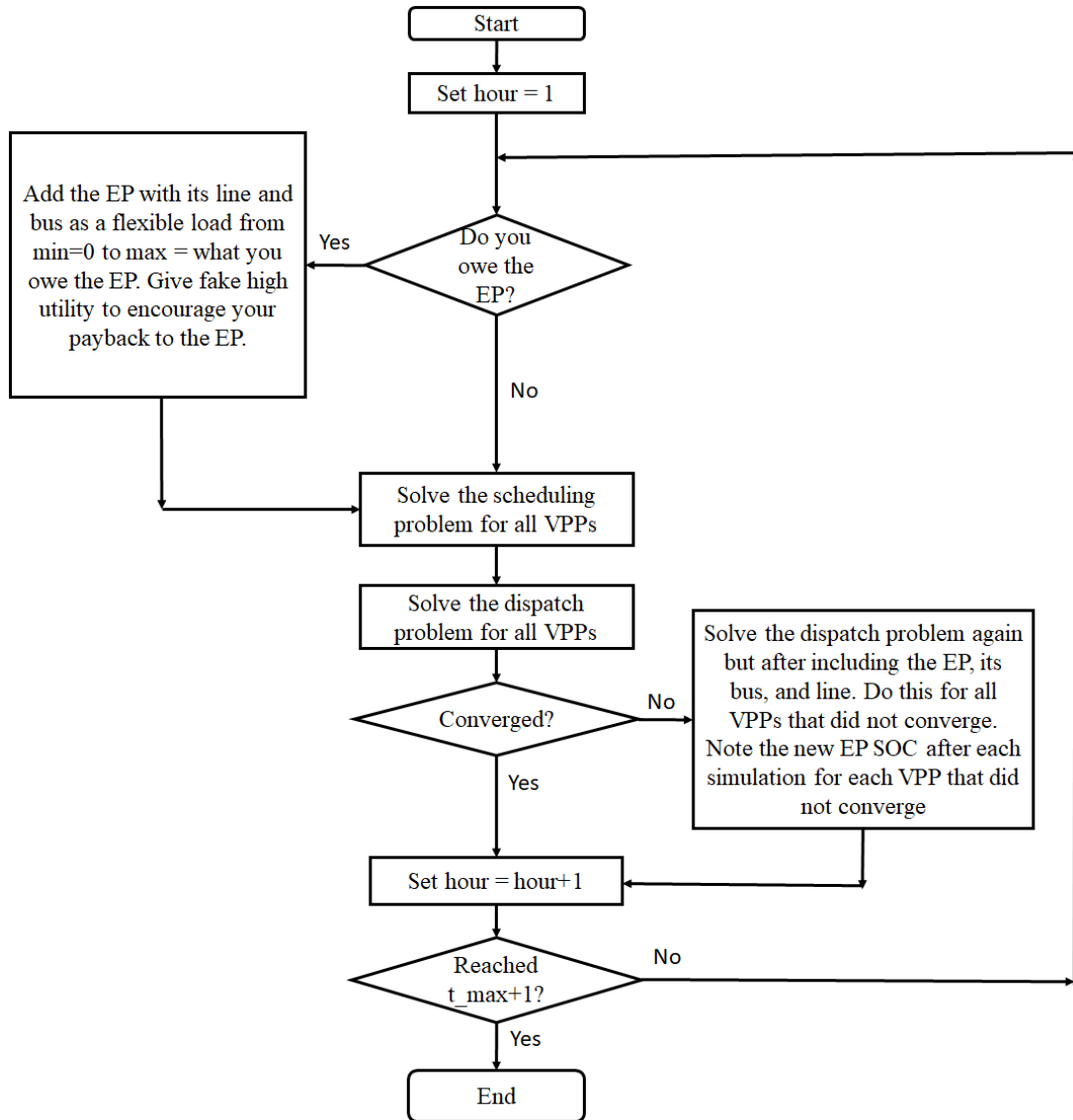


Figure 6-1 EP and VPP flowchart

It can be seen from the flowchart above that the energy pool has a varying behavior depending on the situation. In order for the EP to do the power balance task, the economic aspect has to be considered. Thus, every power transaction between the EP and the VPP shall be recorded just like every transaction between the VPP and the electricity market is recorded. This is not the only issue. The issue is that the EMS of the VPP has to account for all the units involved into the power exchange process for each hour of the RT market

and for the full span of the DA market. If the EP is acting as a storage or power source, then, how can the EMS return back the energy taken from the EP? And if the EP is considered as a load that takes energy from the VPP, then how will it supply the VPP when it has power imbalance? Therefore, the EP will have an alternating behavior being a load or a source based on the situation.

Consider a 24-hour time span for the RT market; knowing that the DA market simulation is unaffected by the EP. That is because any power imbalance will only appear after the RT market clearance at each hour. There might be lack of power after the DA market clearance but that could possibly be substituted by purchasing power from the RT market. Therefore, the EP is only activated after the clearance of each hour of the RT market. The planning will start by setting the hours counter to one then checking whether the VPP owes the EP power or not. If the VPP owes the EP power, the EP has to be connected as a load so that the EMS of the VPP can return back the power taken from the EP back to the EP. If the VPP does not owe the EP any power, the simulation will run normally without considering the EP being connected at all. The scheduling will be done and the RT market will be cleared for that hour. Based on the clearance conditions of the market, the VPP might have a failure at dispatch and it might have power balance. If the power generated is equal to the demand, then, the system has become successfully dispatched at that hour and the counter increases the hours by one and repeats until the 24th hour is reached. In case at dispatch a power imbalance condition is found, the dispatch will be planned again after the EMS runs a dispatch model considering the EP being connected as a source. The EP may be able to cover for the power imbalance and then the system moves to the next hour until the end of the planning scope.

The following two equations govern the process of interaction between the EP and the VPP:

$$EP^{profit} = 0 \quad (6-1)$$

$$VPP_{EP}^{profit} = -\lambda_y^{RT,act} * p^{to,EP} \quad (6-2)$$

Where y stands for the time when the VPP has given power to the EP. The design of the VPP cluster is shown on Figure 6-2.

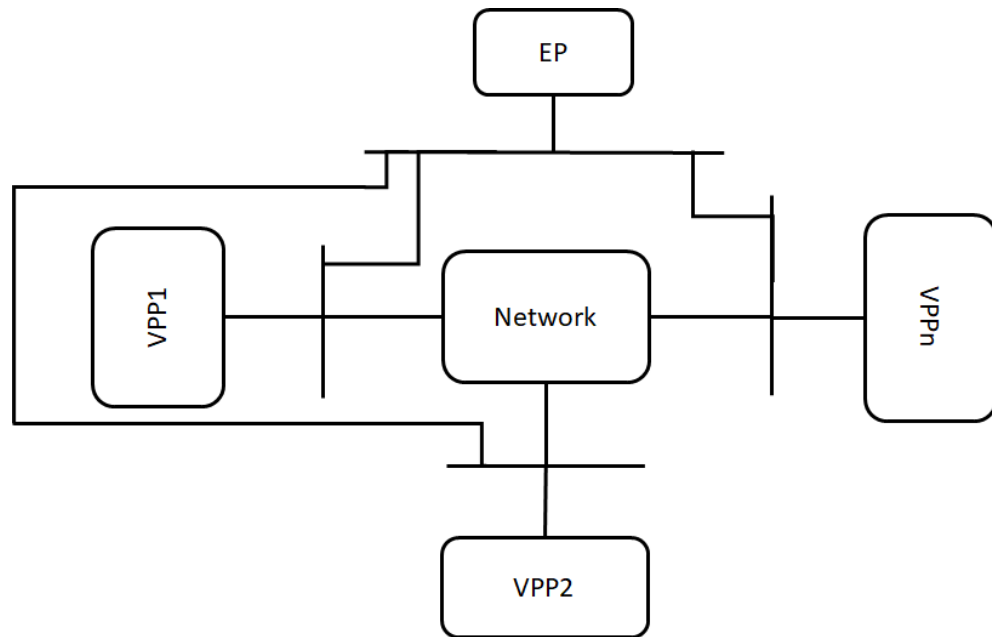


Figure 6-2 VPP Cluster

A powerful EMS shall be used in order to be able to manage the idea of altering the nature of the EP between being a source and a load depending on the situation. Additionally,

keeping track of the SOC of the EP after every transaction with every VPP is not an easy exercise. Each VPP will have the ability to interact with the EP and the ability to consider it a load or a source. Thus, assuming there are 3 VPPs connected, each VPP is participating in both the Day-ahead and real-time markets, and each VPP has the ability to be connected to the EP where the EP acts either as a source or as a load, the communication and control strategies have to be well designed. The design of this system will be done on two stages. First, the connection between the EP and one VPP will be made. The cluster of one VPP and one EP will be simulated to test the design and to prove the concept. Second, three VPPs will be connected to the EP and the EMS strategy will be modified accordingly in order to account for all the possibilities of interaction and the system will be simulated as well. For simulation purposes, the second and third VPPs will be slightly modified versions of the originally studied VPP.

6.4 Water Desalination Unit

In order to add a water desalination unit (WDU) as a specific load type, it must first be modelled as a set of linear equations in order to be incorporated into the VPP MILP model. With reference to [183], the set of linear equations that govern the operation of a WDU are set as follows:

$$Wg_{wt\gamma}^{Tank} + Wg_{wt\gamma}^{WDU} = Wd_{wt\gamma}^{WDU}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-3)$$

$$Wd_{wt\gamma}^{WDU} = Wd_w^{peak} * Wd_{wt}^{profile}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-4)$$

$$Pd_{wt\gamma}^{WDU} = \frac{Wg_{wt\gamma}^{WDU}}{1000} * (PE_w^{WDU} + K_{joule}^{kwh} * PT_w^{WDU}), \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-5)$$

$$0 \leq Wg_{wt\gamma}^{WDU} \leq Wg_w^{HC}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-6)$$

$$Wg_w^{HC} = \frac{Wg_w^{TDC}}{24}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-7)$$

$$Wg_{wt\gamma}^{Tank} = W_{wt\gamma}^{Dis} - W_{wt\gamma}^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-8)$$

$$0 \leq W_{wt\gamma}^{Cha} \leq WPC_w^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-9)$$

$$0 \leq W_{wt\gamma}^{Dis} \leq WPC_w^{Dis}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-10)$$

$$BT_{wt\gamma}^{Cha} \text{ and } BT_{wt\gamma}^{Dis} \text{ are binary}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-11)$$

$$BT_{wt\gamma}^{Cha} + BT_{wt\gamma}^{Dis} \leq 1, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-12)$$

$$W_{wt\gamma}^{Cha} \leq M * BT_{wt\gamma}^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-13)$$

$$W_{wt\gamma}^{Dis} \leq M * BT_{wt\gamma}^{Dis}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-14)$$

$$W_{wt\gamma}^{Tank} = W_{w(t-1)\gamma}^{Tank} + W_{wt\gamma}^{Cha} * \Delta t - W_{wt\gamma}^{Dis} * \Delta t, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-15)$$

$$0 \leq W_{wt\gamma}^{Tank} \leq W C_w^{Tank}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-16)$$

$$W_{wt\gamma}^{Dis} * \Delta t \leq W_{w(t-1)\gamma}^{Tank}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (6-17)$$

$$\sum_t W_{wt\gamma}^{Dis} * \Delta t = \sum_t W_{wt\gamma}^{Cha} * \Delta t, \forall w \in \Omega^w, \forall \gamma \in \Pi^{RT} \quad (6-18)$$

Where $W_{wt\gamma}^{Tank}$ refers to the water generated by the tank of the WDU [m^3], $W_{wt\gamma}^{WDU}$ refers to the water generated by the WDU [m^3], $Pd_{wt\gamma}^{WDU}$ is the total equivalent electric demand of the WDU [MW], $W_{wt\gamma}^{Dis}$ is the discharged water from the tank of the WDU [m^3], $W_{wt\gamma}^{Cha}$ is the charged water to the tank of the WDU [m^3], $BT_{wt\gamma}^{Cha}$ is a charging indicator of the tank of the WDU, $BT_{wt\gamma}^{Dis}$ is a discharging indicator of the tank of the WDU, $W_{wt\gamma}^{Tank}$ is the water stored in the tank of the WDU [m^3], $Wd_{wt\gamma}^{WDU}$ is the water demanded from the WDU [m^3], Wd_w^{peak} is the daily peak water demand of the WDU [m^3], $Wd_{wt}^{profile}$ is the normalized water demanded of the WDU, PE_w^{WDU} is the electric power consumption of the WDU [kW/m^3], K_{joule}^{kwh} is a conversion factor from Mega Joule to kW [0.277778], PT_w^{WDU} is the thermal energy consumption of the WDU [MJ/m^3], Wg_w^{HC} is the hourly maximum water generation capacity of the WDU [m^3/h], Wg_w^{TDC} is the total daily water generation capacity of the WDU [m^3], WPC_w^{Cha} is the water charging capacity of the tank of the WDU

$[m^3]$, WPC_w^{Dis} is the water discharging capacity of the tank of the WDU $[m^3]$, M a big value positive constant, and WC_w^{Tank} is the total capacity of the tank of the WDU $[m^3]$.

The first equation states that the water generated by the WDU and its tank are equal to the water demanded. The second equation calculates the hourly water demand based on a normalized profile and a peak demand value. The total equivalent electric power consumption of the WDU is calculated through the third equation while the fourth equation limits the water generation of the WDU to the maximum possible water generation capacity of the WDU. The maximum hourly water generation capacity of the WDU is calculated by dividing the total daily capacity of generation by the 24 hours of the day as per the fifth equation. The sixth equation defines the water generated by the tank as the difference between the water discharged and the water charged to the tank and the two equations after that limit the charging and discharging capacities respectively. The 11th, 12th and 13th equations force the tank to either charge or discharge while M is a big value positive number to avoid any conflict between those equations and equations seven and eight.

The next three equations define the water level in the tank, its maximum and minimum states, and that the maximum water discharged cannot go beyond the existing water level in the tank. Lastly, the last equation is specifically related to this type of load. For water desalination units, there is a health consideration of the duration of water storage into the tanks. To avoid storing water into the tanks for a long period of time, it must be ensured that the water level in the tank at the beginning and the end of the day are the same. This means that all the water that has got into the tank has flown out of the tank within one day

and thus it was not stored for more than one day. Figure 6-3 shows the schematic of a water desalination unit that involves a water tank. The untreated water gets into the water desalination unit for pretreatment, desalination and stabilization. This process requires electrical energy and could require thermal energy too. The brine is then discarded while the fresh water is either moved to the storage unit or supplied to the demand directly.

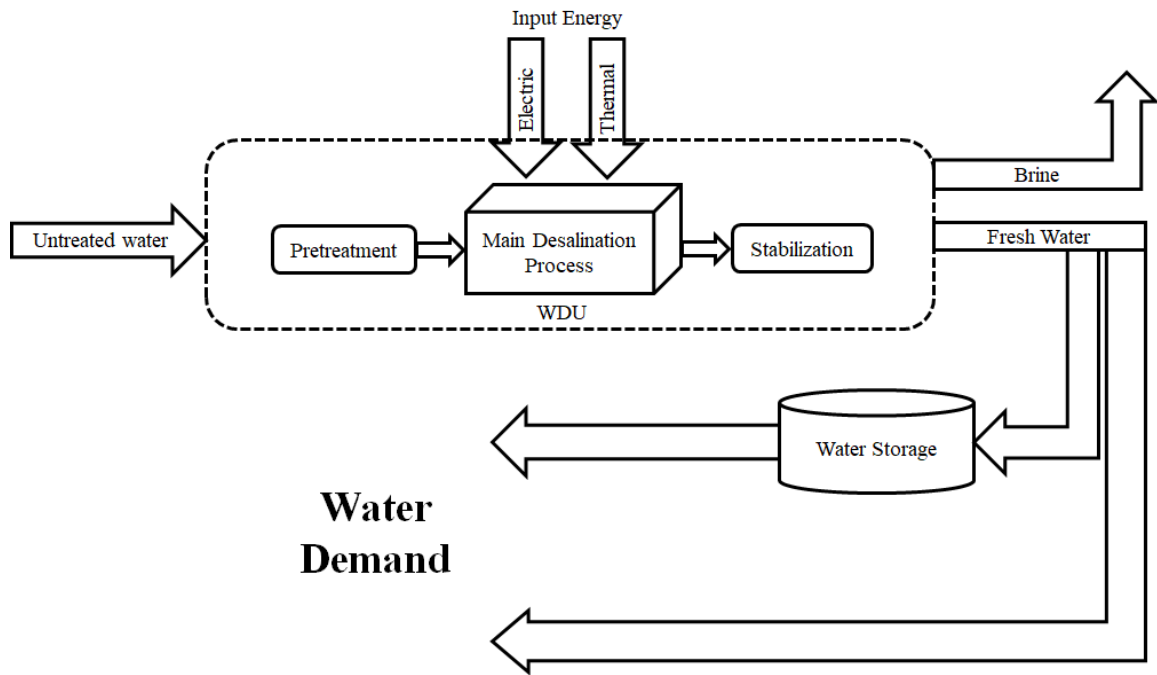


Figure 6-3 Water desalination unit schematic

The input data of the WDU is presented on Table 6-1 and Figure 6-4.

Table 6-1 Water desalination unit data	
Bus location	5
Technology	Reverse Osmosis
Feed water	Brackish

Energy consumption (electric) [kW/m ³]	2.2
Energy consumption (thermal) [MJ/m ³]	0
Production capacity, daily [m ³ /day]	200,000
Storage tank charging limit [m ³ /h]	500
Storage tank discharging limit [m ³ /h]	500
Storage tank capacity [m ³]	2500
Daily water demand, peak [m ³ /h]	7000

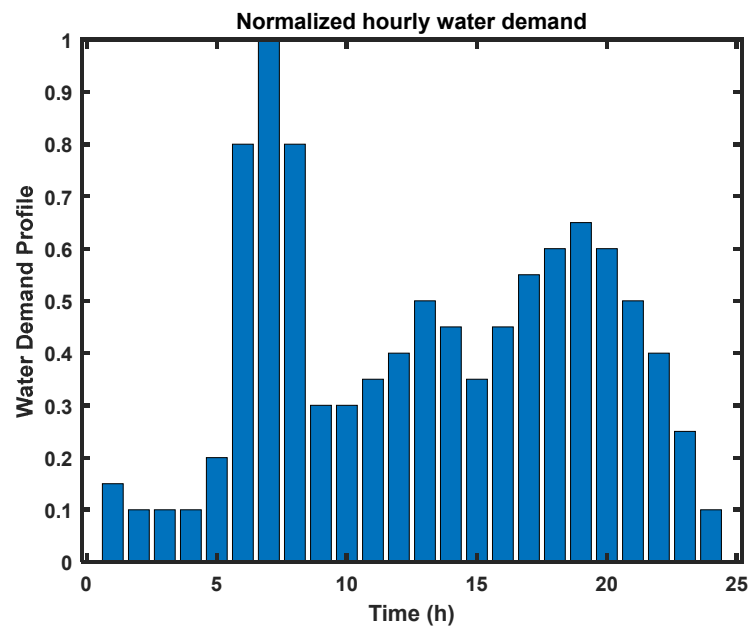


Figure 6-4 Normalized hourly water demand

By this, the WDU can be included into the VPP after the assignment of a utility value that is obtained by supplying this load.

6.5 Reliability Objective

The considered VPP considers risk by the involvement of the CVaR. Nevertheless, it still fails a lot in participating into the RT market which is a major issue. This failure is due to the fact that the VPP supplies its demand and tries to make the maximum profit out of that. After that, it tries to make the maximum profit through the trading in both the Day-ahead and real-time markets. If the price of the day-ahead market is higher than the price of the real-time market, the VPP will most probably try to sell as much as possible in the day-ahead market and recover that in the real-time market. This is very risky when the VPP sells more than its generating power in the day-ahead market based on the expectation that it can recover that by purchasing in the real-time market at a lower price.

The reason why CVaR still fails to address such cases though it is expected to address them is the fact that CVaR considers the worst scenarios. In the simulation presented in the previous sections, it was set to select the worst 20% scenarios. Assume that at a specific hour, the DA price scenarios are (41\$, 42\$, 43\$, 44\$, 45\$) while the RT price scenarios are (35\$, 36\$, 37\$, 38\$, 39\$). Now, if the VPP decides to sell 100 MW at that hour in the DA market, it will earn 4100\$ in the worst-case scenario which is the worst 20% scenarios in this case as well. If the VPP decides to purchase this 100 MW in the RT market, it will pay 3900\$ in the worst case or worst 20% scenarios in terms of impact on profit. Therefore, even if CVaR forces the VPP to consider the worst 20% of the scenarios, the MILP will still find it profitable in this case to sell as much as possible in the DA market and purchase it back from the RT market. If at the RT market, at the same hour, the cleared market price

is found to be 34\$, the VPP will fail to participate into the market and thus it could have power imbalance.

Therefore, there must be a stronger reliability set of constraints or objective that governs this kind of situation. Therefore, another objective for this MILP will be the reliability of participation into the markets at all hours if possible. A developed and proposed reliability set of constraints is introduced through the set of equations below.

$$\sum_{c \in \Omega^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega^S} p_{st\omega\gamma}^S - \sum_{d \in \Omega^D} p_{dt\omega\gamma}^D - p_{t\omega}^{DA} = p_{t\omega\gamma}^{sum}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (6-19)$$

$$p_{t\omega\gamma}^{sum} \leq 10000 B_{t\omega\gamma}^{sum1}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (6-20)$$

$$p_{t\omega\gamma}^{sum} \geq -10000 B_{t\omega\gamma}^{sum2}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (6-21)$$

$$B_{t\omega\gamma}^{sum1} + B_{t\omega\gamma}^{sum2} \leq 1, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (6-22)$$

$$X_t^{lim} = \frac{\sum_{\omega\gamma} DA \text{ scenarios} - \sum_{\gamma} \text{highest RT scenarios}}{\text{average}(DA \text{ scenarios})} * 100, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (6-23)$$

$$2\beta - X_t^{lim} \leq 1000 B_{t\omega\gamma}^{sum1}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (6-24)$$

The first equation calculates the net power value for each hour including the power traded with the DA market. The final result will be either having a positive value or a negative value for that summation. If the value is positive, it means the power generated is more than or equal to the power demanded including the power traded. If the value is negative, it means that the VPP is going to risk being on a negative generation side planning to recover that in the RT market. By doing this, the risk status is detected. Therefore, if the VPP plans to sell more than its generating power in the DA market hoping to recover that in the RT market, the power summation will be negative.

The second and third equations introduce binary variables that would detect the sign of the power summation. If the power summation is positive, the first binary variable will be equal to one. If the power summation is negative, the second binary variable will be equal to one. To avoid the case when both binary variables can be one, the fourth equation is introduced to force only one binary variable to be equal to one at most. After detecting the sign of the summation of power, there must be a criterion to decide when to allow the sign to be negative i.e., when to risk, and when not to. The fifth equation calculates X_t^{lim} as the difference between all the DA scenarios and the worst/highest RT scenarios. It must be noted however that the number of scenarios should be equivalent. For example, if the DA scenarios are five, then, the highest RT scenarios, in terms of price value, shall be five scenarios. Or similar scaling is required based on the number of scenarios considered. Then, this difference is calculated as a percentage of the average DA price scenarios.

Therefore, this equation considers the percent difference between the DA market prices and the RT market prices. If after considering the highest scenarios of the RT market, the average percent difference is positive, it means that the model has detected a case where the VPP would most probably be willing to risk by doing maximum power sale in the DA market and then purchasing it back from the RT market. This is because, on average, the highest prices of the RT market are still lower than those of the DA market. Supposing that the average percent difference is 1%, would this imply that there should be a reliability constraint in order to stop this? The developed and proposed methodology sets a percent limit criterion that decides when to stop and when to allow this behavior. The sixth equation states that if that difference is less than or equal to 2β , where 2 stands for a percent difference of 2% and β is the same weighing factor of the CVaR, then the power summation is forced to be greater than or equal to zero. The weighing factor can be different from that of CVaR but it has been selected to be the same in order to have one scaling factor for risk consideration. The higher the weighing factor, the more conservative this proposed set of constraints is. If β is set to a value of two, it means that any percent difference of 4% or lower will be forbidden from risking. In other words, in cases where the percent difference is a small positive value or even a negative value, the VPP should not be risking for a small amount of profit. If the profit exceeds a barrier, of 2% in here, it can be allowed to risk due to the high profit margin that is expected from the considered scenarios. The 2% can be selected differently but it has been found acceptable in here to avoid cutting the profit dramatically while increasing the reliability. However, the weighing factor has been added for scalability of risk control. All the constant values used in the equations are big numbers that allow for all possible range of positive or negative values that are expected.

A similar concept to the proposed reliability constraints proposed is the chance constrained optimization. In chance constrained optimization however, the limit is not set by a fixed value as proposed here; though the proposed fixed value here is controlled by a weighing factor. The chance constrained optimization optimizes an objective subject to the following constraints, [193]:

$$\mathbb{P}\{g_j(x, \varpi) \geq 0, j = 1, 2, \dots, m\} \geq \mathbb{p}_j \quad (6-25)$$

Where x represents the deterministic variables and ϖ represents the random variables. The constraint checks that the probability of all the j constraints is higher than the probability values $\mathbb{p}_j$. This is called individual chance constrained optimization where each constrained is checked against individual probability value. If multiple constraints are checked against one probability value, this is called joint chance constrained optimization. In the case of the proposed reliability constraints, the constraints are not checked against a probability level but rather a weighted value which could be thought of as a probability level.

In [194], the benefits and challenges of using chance constrained optimization is discussed and compared to robust and stochastic optimization. The chance constrained optimization is proposed as a balance between the complexity of stochastic optimization and the conservativeness of robust optimization. Detailed explanation of further types and the mathematical modelling of chance constrained optimization is presented in [195]-[197].

Comparing the proposed reliability constraints to the chance constrained optimization proves multiple benefits to the proposed reliability constraints. As per [193], chance constraint optimization is not an easy optimization to solve. This difficulty exists in small scale problems as well. Therefore, multiple approximation methods have been introduced in order to overcome this difficulty. When the inequality constraints are not explicitly available, it becomes a challenge to solve chance constrained optimization problems, [194]. This is in addition to the fact that there is no general method for solving chance constrained optimization problems. This is because there are no specific properties that can be made regarding chance constrained optimization problems such as concavity, continuity or differentiation.

The proposed reliability constraints are very simple to apply as they do not require interaction with probability of constraints, random variables, or any of the issues addressed in the chance constrained optimization. It is a simple set of constraints that decide the conservativeness of the system based on the decision of the operator. That decision is simply based on the forecasted profit difference between the RT and DA market prices. Higher difference means any forecast error is minor, compared to the large difference in prices, which means that the operator can make more risky decisions with less concern. In contrary, small differences in prices mean that any small forecast error is significant, compared to the small price difference, which should make the operator of the VPP more conservative to avoid failure.

6.6 Multi-Objective VPP with Specific Load

After simulating the proposed multi-objective model with the inclusion of a water desalination unit as part of the flexible demand, the results were found to be as below. First, the most obvious change is that the power exchange has changed dramatically and this is due to the reliability constraints imposed. It can be seen that the VPP has decided to mostly purchase power in the DA market. More specifically, at the four hours where the model failed earlier, the scenario has changed. Previously, the VPP decided to sell at the maximum limit in the DA market at the 12th, 18th, 20th and 23rd hours and it failed to recover that in the RT market. After imposing the new reliability rules, it can be found that the VPP decided to buy power instead at the 12th and the 23rd hours. It also has decided not to buy nor to sell at the 20th hour. This has resulted in avoiding the failure at those specific hours. This can be clearly seen on Figure 6-5.

The situation has not changed for the 18th hour though. The failure at the 18th hour can be avoided by increasing the weight at the reliability constraints but this would definitely be on the cost of the net profit. On Table 6-4, the profit is found to be reduced compared to the case without reliability constraints. The drop in profit is however expected due to the increase in reliability. Therefore, there is a tradeoff between the reliability and the expected net profit which is tunable by the VPP operator. The drop in profit is justified as multiple failures to participate into the electricity markets could lead to tremendous drop in profit or even big loss.

Table 6-2 Power Exchange – multi-objective with specific load

	Conventional Generator (MW)	Renewable Source (MW)	Storage Energy (MW)	Total Generation (MW)	DA Power (MW)	RT Power (MW)	Demand (MW)
t1	170.00	1.83	100.00	271.83	-200.00	0.00	471.83
t2	230.00	0.85	69.56	300.41	-200.00	0.00	500.41
t3	290.00	0.00	2.90	292.90	-200.00	0.00	492.90
t4	294.00	0.69	0.00	294.69	-200.00	0.00	494.69
t5	294.00	0.00	7.54	301.54	-200.00	0.00	501.54
t6	294.00	0.00	0.00	294.00	-200.00	0.00	494.00
t7	294.00	0.00	0.00	294.00	0.00	-200.00	494.00
t8	294.00	1.25	0.00	295.25	0.00	-200.00	495.25
t9	294.00	0.36	0.00	294.36	-200.00	0.00	494.36
t10	294.00	0.00	0.00	294.00	-200.00	0.00	494.00
t11	294.00	5.71	0.00	299.71	-200.00	0.00	499.71
t12	294.00	3.62	0.00	297.62	-200.00	0.00	497.62
t13	294.00	5.65	0.00	299.65	0.00	-126.70	426.35
t14	294.00	8.52	0.00	302.52	300.00	-500.00	502.52
t15	294.00	8.84	0.00	302.84	-200.00	0.00	502.84
t16	294.00	7.01	0.00	301.01	300.00	-500.00	501.01
t17	294.00	12.51	0.00	306.51	300.00	-500.00	506.51
t18	294.00	14.74	0.00	308.74	300.00	0.00	508.74
t19	294.00	9.64	0.00	303.64	300.00	-500.00	503.64
t20	294.00	6.67	0.00	300.67	0.00	0.00	300.67

	Conventional Generator (MW)	Renewable Source (MW)	Storage Energy (MW)	Total Generation (MW)	DA Power (MW)	RT Power (MW)	Demand (MW)
t21	294.00	3.11	0.00	297.11	0.00	-200.00	497.11
t22	294.00	10.03	0.00	304.03	300.00	-500.00	504.03
t23	294.00	11.10	0.00	305.10	-200.00	0.00	505.10
t24	294.00	11.26	0.00	305.26	-200.00	0.00	505.26

Table 6-3 Hourly net profit without DA market revenue – multi-objective with specific load

Hour	Profit (utility – generator cost) (\$)	RT Revenue (\$)	Net profit (\$)
h1	25,277.52	0.00	25,277.52
h2	25,924.64	0.00	25,924.64
h3	22,786.22	0.00	22,786.22
h4	22,700.68	0.00	22,700.68
h5	23,084.89	0.00	23,084.89
h6	22,661.90	0.00	22,661.90
h7	22,661.90	-7,926.00	14,735.90
h8	22,731.94	-7,102.00	15,629.94
h9	17,456.81	0.00	17,456.81
h10	17,680.78	0.00	17,680.78
h11	17,971.99	0.00	17,971.99
h12	17,858.48	0.00	17,858.48
h13	14,377.69	-6,050.16	8,327.53
h14	18,048.49	-20,260.00	-2,211.51
h15	18,023.67	0.00	18,023.67
h16	17,948.92	-17,460.00	488.92
h17	21,693.62	-17,995.00	3,698.62
h18	21,814.75	0.00	21,814.75
h19	21,531.00	-18,820.00	2,711.00
h20	9,555.84	0.00	9,555.84
h21	21,180.29	-7,546.00	13,634.29
h22	21,597.94	-17,185.00	4,412.94
h23	21,663.52	0.00	21,663.52
h24	21,697.65	0.00	21,697.65

Table 6-4 Hourly net profit without DA market revenue

Utility and RT Profit (\$)	DA Market Net Profit (\$)	Net profit (\$)
367,586.97	-8,631	358,955.97

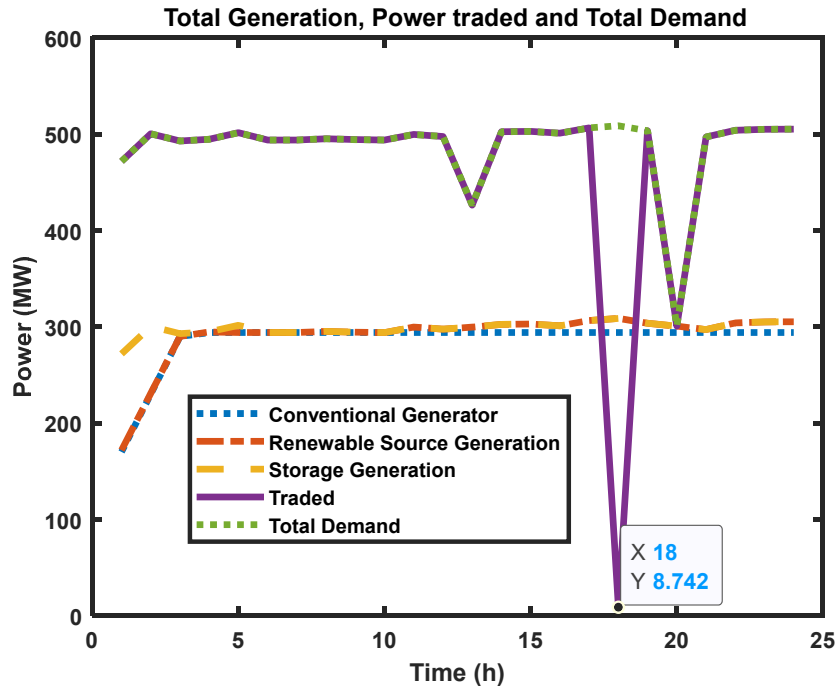


Figure 6-5 Total generation, power traded and demand – multi-objective with specific load

Thus, the reliability constraints were very effective at remedying the issue of multiple failure rates. After proving the effectiveness of the proposed reliability objective, a specific focus should be given to the newly introduced specific load type. To analyze the behavior of the WDU, its water and electricity interaction should be presented and assessed.

Table 6-5 Water desalination unit water and power exchange

Hour	WDU water generation (m3)	Tank water generation (m3)	Electric demand (MW)
t1	550.00	500.00	1.21
t2	700.00	0.00	1.54
t3	1,200.00	-500.00	2.64
t4	1,200.00	-500.00	2.64
t5	1,900.00	-500.00	4.18
t6	6,100.00	-500.00	13.42
t7	6,500.00	500.00	14.30
t8	6,100.00	-500.00	13.42
t9	2,100.00	0.00	4.62
t10	2,100.00	0.00	4.62
t11	2,450.00	0.00	5.39
t12	2,800.00	0.00	6.16
t13	3,000.00	500.00	6.60
t14	3,650.00	-500.00	8.03
t15	2,450.00	0.00	5.39
t16	3,150.00	0.00	6.93
t17	3,350.00	500.00	7.37
t18	3,700.00	500.00	8.14
t19	4,050.00	500.00	8.91
t20	3,700.00	500.00	8.14
t21	3,104.32	395.68	6.83
t22	2,838.27	-38.27	6.24
t23	2,107.41	-357.41	4.64
t24	1,200.00	-500.00	2.64
Total	70,000.00	0.00	154.00

Table 6-6 Water desalination unit tank water level

Hour	Tank water level (m3)	Water charged (m3)	Water discharged (m3)
t1	500.00	0.00	500.00
t2	500.00	0.00	0.00
t3	1,000.00	500.00	0.00
t4	1,500.00	500.00	0.00
t5	2,000.00	500.00	0.00
t6	2,500.00	500.00	0.00
t7	2,000.00	0.00	500.00
t8	2,500.00	500.00	0.00
t9	2,500.00	0.00	0.00
t10	2,500.00	0.00	0.00
t11	2,500.00	0.00	0.00
t12	2,500.00	0.00	0.00
t13	2,000.00	0.00	500.00
t14	2,500.00	500.00	0.00
t15	2,500.00	0.00	0.00
t16	2,500.00	0.00	0.00
t17	2,000.00	0.00	500.00
t18	1,500.00	0.00	500.00
t19	1,000.00	0.00	500.00
t20	500.00	0.00	500.00
t21	104.32	0.00	395.68
t22	142.59	38.27	0.00
t23	500.00	357.41	0.00
t24	1,000.00	500.00	0.00
Total		3,895.68	3,895.68

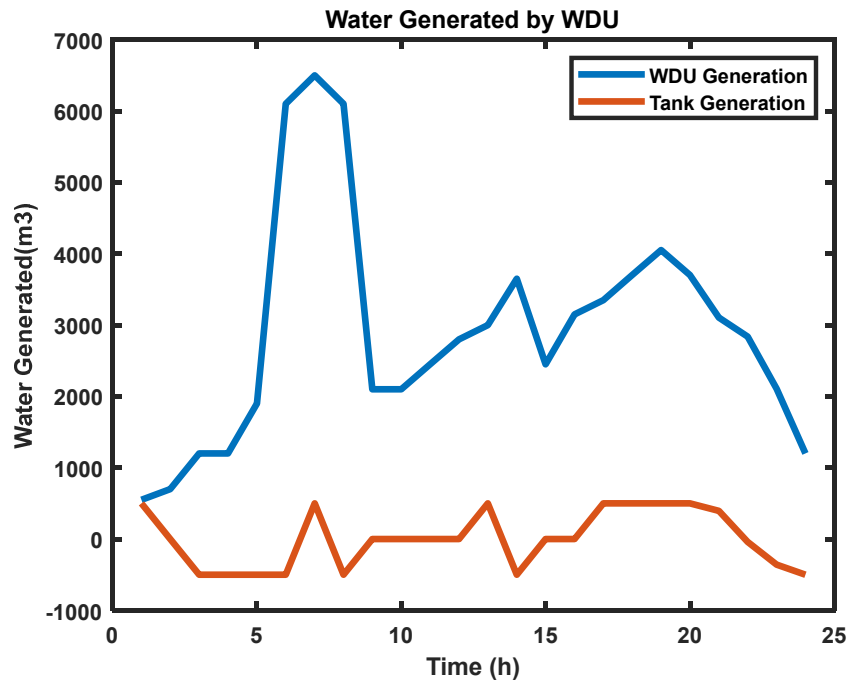


Figure 6-6 Water desalination unit water generation

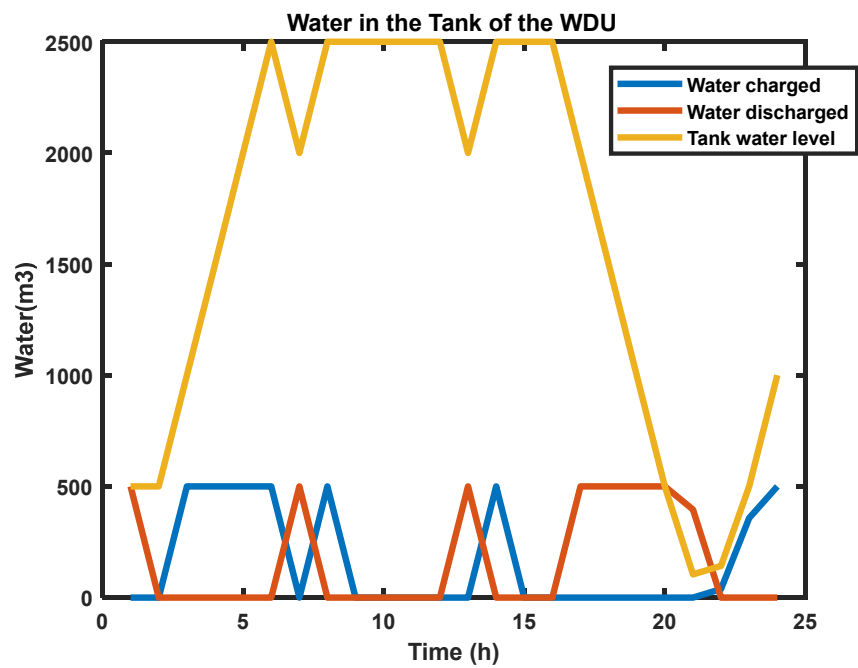


Figure 6-7 WDU tank charge and discharge

The tank of the WDU has a total water charge and discharge that is equal to zero which is a requirement in the design. This means that there is no water stored in the tank in the overall process over a 24-hours span. This is due to health considerations. Thus, the tank started with 1000 cubic meters of water at the zeroth hour and it ended up with the same level by the end of the 24th hour. Which can also be translated as a total tank generation of zero over the day. The total water generated by the WDU over the day is 70,000 cubic meters of water. This has supplied the water demand completely without failures. Lastly, Figure 6-8 shows the relationship between the water generated and the electric demand. It can be noticed that the relationship is linear and this is due to the fixed electric demand value that is given in kW/m³. The total electric demand of the WDU during the 24-hours span is 154 MW. This demand has not affected the power exchange in the Day-ahead and real-time markets due to its small amount in addition to the fact that the MILP is already at the maximum limits of trade with the markets due to the high profit found in that strategy. This however has slightly affected the revenue made from the utility as it is a new load introduced and it has its own utility which definitely affects the decision making of the MILP on which load to feed for higher profitability.

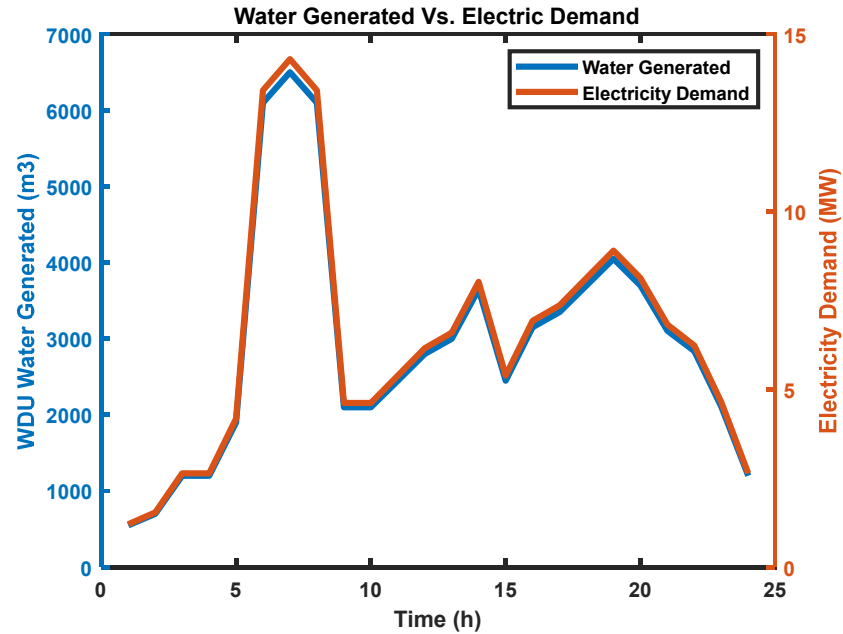


Figure 6-8 Water generated Vs. electric demand

6.7 Self-Controlled Water Desalination Unit

The water desalination unit has great importance and part of this importance is being used as a storage medium. To get the best benefit out of the WDU in terms of energy storage, it has to be efficient in doing this job. This means that the WDU has to incur the least possible cost of electricity while supplying the water demand. The tank serves as a storage medium that manages the fluctuations of demand while helping in reducing the total electricity cost incurred by the WDU. To do this, a centralized control scheme of the VPP may not be applicable in this case. Therefore, the WDU will try to manage optimizing its own cost and supply opposing the centralized control scheme of the VPP. Nevertheless, the centralized control scheme will still be applicable to the rest of the system.

This is similar to the comprehensive control scheme. As discussed earlier, the control schemes in VPPs are divided into three types: centralized, distributed and comprehensive control schemes. The centralized control scheme is where there is a centralized controller that optimizes the objectives of the VPP as a whole. In distributed control, each member of the VPP optimizes its own objectives separately. In comprehensive control, a mixed control scheme between the centralized and the distributed is adapted. This is similar to the case where the WDU optimizes its own objective aside from the centralized control scheme of the VPP.

A similar concept to the comprehensive control is the transactive control concept. In fact, this concept is divided to three parts where the first is the transactive network management, the second is the transactive control, and the third is the peer-to-peer market, [184]. Transactive network management is related to the methodology of managing the network such as being a load aggregator or a microgrid. Transactive control is very similar to the fully distributed control scheme. Lastly, the peer-to-peer (P2P) is a form of comprehensive control where suppliers and customers interact directly under a supervisory control scheme. This P2P market has another variant called the community-based market where each peer is replaced by a small community, [185]. In P2P, community, or comprehensive control, there is usually two levels of control or more. The first level is the low level between the prosumers and the second is concerned with the network constraints which is managed by the distribution system operator (DSO), [186]-[188].

Each architecture of control has its own advantages and disadvantages. In [189], the authors review multiple architectures proposed for the P2P market where each architecture proposes a different number of layers. There are 3 layers, 5 layers, and 7 layers architectures. These layers can be a regulation layer, communication layer, market layer, user layer, and so on. Examples of mathematical models used to solve such transactive energy markets are presented in [190] and [191]. Lastly, four practical projects concerning transactive energy are presented in [192]. Those four projects are: the Grise-Wise Olympic Peninsula, the Grid-Smart demonstration, the Pacific Northwest demonstration, and the power matching city projects.

In order to analyze the behavior of the WDU, three scenarios will be simulated. In the first scenario, the system will be simulated without the inclusion of a WDU. In the second scenario, the system will be simulated having a WDU connected and the control scheme will be a centralized one where the VPP will try to maximize its profit. Lastly, in the third scenario, the system will be the same as the second scenario but the control scheme will be comprehensive where the VPP will try to maximize its profit while the WDU will try to reduce its utility cost.

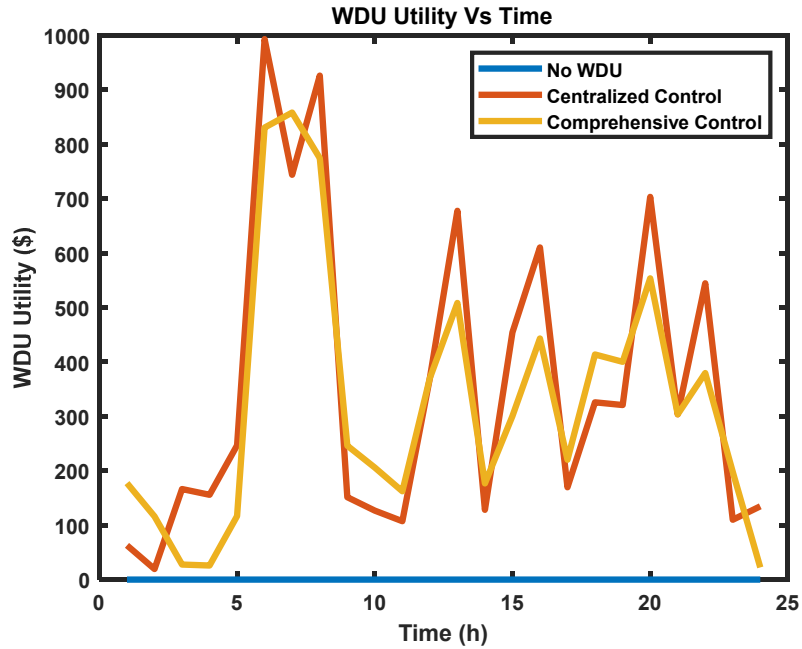


Figure 6-9 WDU Utility – 3 scenarios

It can be seen from Figure 6-9 that there is no utility for the first scenario since there is no WDU connected at all. In the second scenario, the utility paid by the WDU is higher than the utility paid by the WDU in the third scenario at most of the hours. This makes sense as in the third scenario, the WDU is trying to reduce its expenses while supplying the demand profile with no issues. The difference and percent saving are shown on Table 6-7.

Table 6-7 WDU utility, profit and energy (comprehensive and centralized control)

	No WDU	Centralized Control	Comprehensive Control	% Difference
WDU Utility (\$)	0	8,551.40	7,829.80	9.22%
Total Profit (\$)	359,330.21	359,607.60	358,916.48	0.2%
WDU Energy (MWh)	0	154	154	0%

By analyzing Table 6-7, the total profit of the VPP for the second scenario is higher than the first one and this is logical since in the second scenario, the WDU will be added as a

load that will pay utility to the VPP which will generate profit to the VPP. The third scenario however has lower profit to the VPP compared to the second one. This is because the WDU optimizes its own cost independently from the VPP. When the WDU pays less, the VPP profit is reduced. The impact in percentage is 0.2% increase of VPP profit for the centralized scenario compared to the comprehensive one. Which is reflected onto the WDU as 9.22% more cost the WDU has to incur in the centralized scenario compared to the comprehensive one. Lastly, the electric demand for the second and third scenarios is the same. This is expected since the water load profile is fixed and the power consumption is taken as a linear function of the water demand.

6.8 Self-Controlled Flexible Water Desalination Units

The WDU considered in the previous sections was limited in size compared to the rest of the VPP components. Additionally, the water demand profile was not a flexible profile. In this section, the WDU will be scaled up to have a relative size compared to the rest of the VPP components and the water load profile will feature some flexibility. Therefore, there will be four scenarios studied in this section: a centralized control scheme with a fixed water load profile, a comprehensive control scheme with a fixed water load profile, a centralized control scheme with a flexible water load profile, and a comprehensive control scheme with a flexible water load profile.

As shown on Table 6-8, the scaled up WDU that will be considered in this section is ten times the sizes of the WDU considered in the previous sections. Thus, at the peak water

demand, the electric demand of the WDU would be 154 MW which is a relative demand compared to the rest of the VPP components.

Table 6-8 Scaled up WDU

	Small WDU	Scaled WDU
Bus location	5	5
Technology	Reverse Osmosis	Reverse Osmosis
Feed water	Brackish	Brackish
Energy consumption (electric) [kW/m ³]	2.2	2.2
Energy consumption (thermal) [MJ/m ³]	0	0
Production capacity, daily [m ³ /day]	200,000	2,000,000
Storage tank charging limit [m ³ /h]	500	5,000
Storage tank discharging limit [m ³ /h]	500	5,000
Storage tank capacity [m ³]	2500	25,000
Daily water demand, peak [m ³ /h]	7000	70,000

To make a flexible load profile, the original water load profile will be allowed to go 50% below the original profile and 50% above the original profile. This means that the water load profile will range from 50% to 150% of the original profile as shown on Figure 6-27.

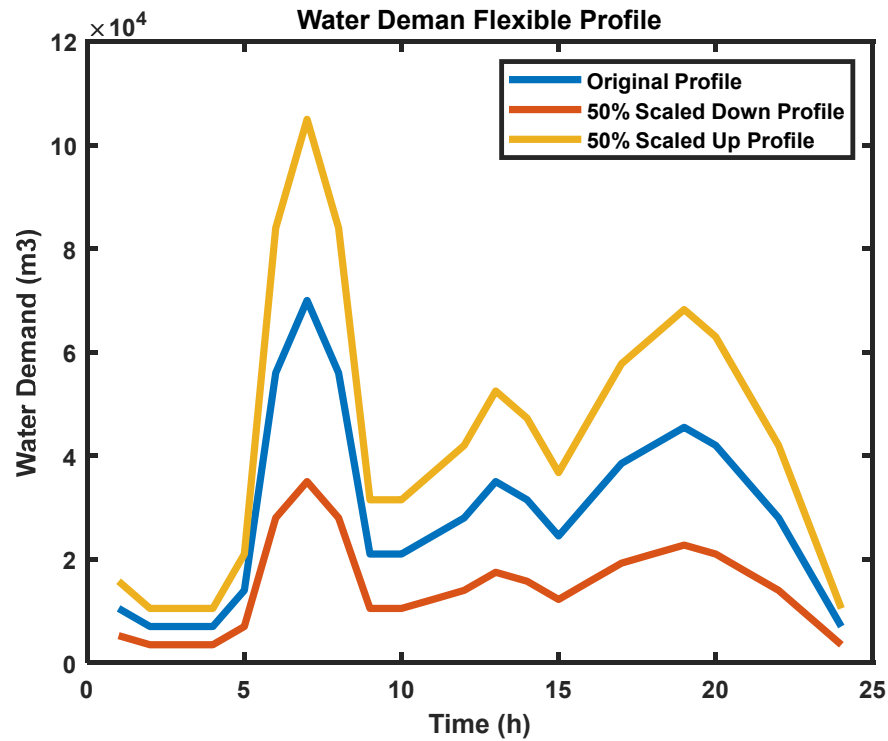


Figure 6-10 Flexible Water Load Profile

6.8.1 Centralized Control, Fixed Demand

In this section, the centralized control scheme with fixed demand is shown for the scaled up WDU, referred to as the first scenario, and it can be seen on Figure 6-11 that the demand is matching the generation at all points except the 18th and the 20th hours which is a similar behavior to the original system with the small size WDU except that there is a major change at the 20th hour. The VPP has got back to a failure state at the 20th hour. This is because of

the expansion in size of the WDU. Figure 6-12 and Figure 6-13 show the water generated by the WDU and its tank in addition to the tank water level and its charge and discharge rates respectively.

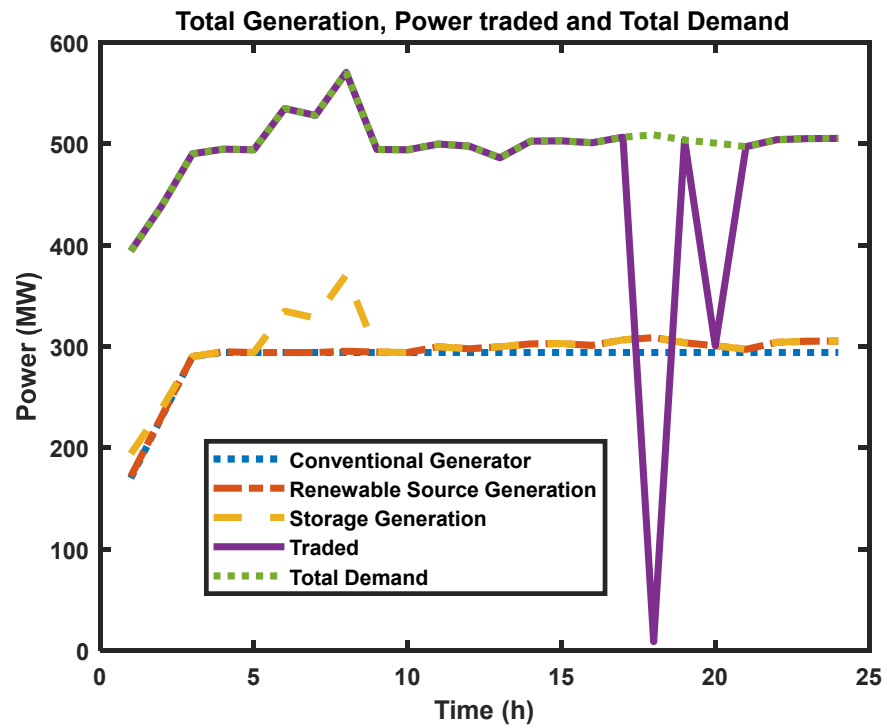


Figure 6-11 Total Generation, Power traded and Total Demand, Centralized Control, Fixed Demand

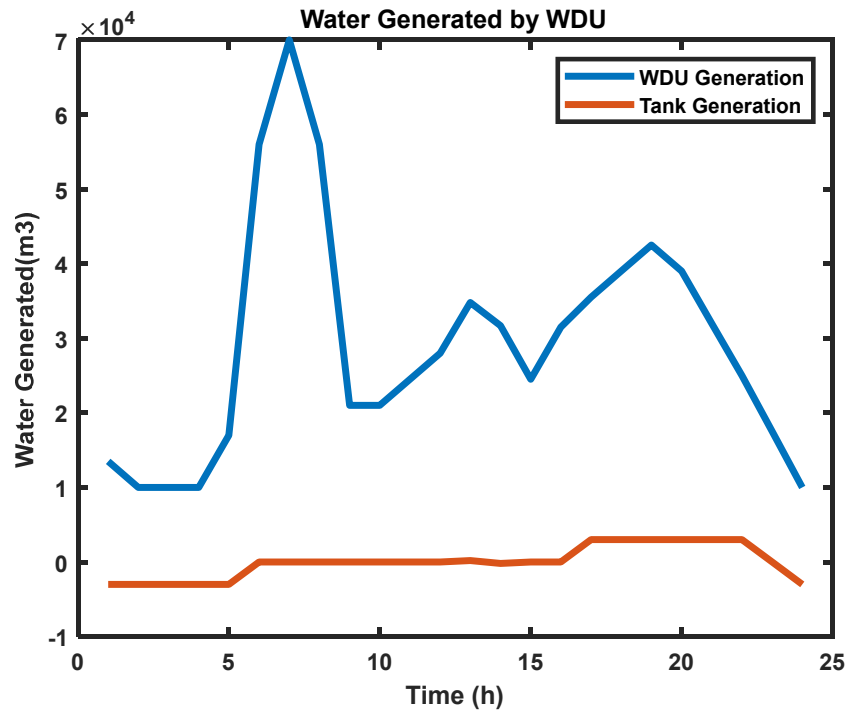


Figure 6-12 Water Generated by WDU, Centralized Control, Fixed Demand

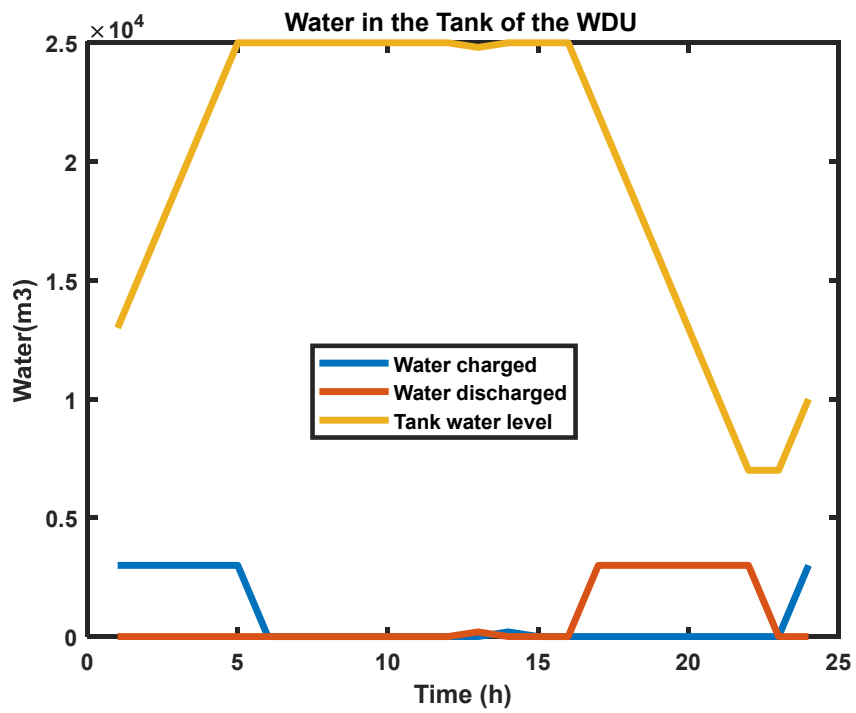


Figure 6-13 Water in the Tank of the WDU, Centralized Control, Fixed Demand

6.8.2 Comprehensive Control, Fixed Demand

In this section, the comprehensive control scheme with fixed demand is shown for the scaled up WDU, referred to as the second scenario, and it can be seen on Figure 6-14 that the behavior is generally similar to the first scenario. Figure 6-15 and Figure 6-16 show the water generated by the WDU and its tank in addition to the tank water level and its charge and discharge rates respectively. The figures are very similar to the first scenario except for the water tank behavior which is different. A comparison of the four scenarios will be made in section 6.8.5.

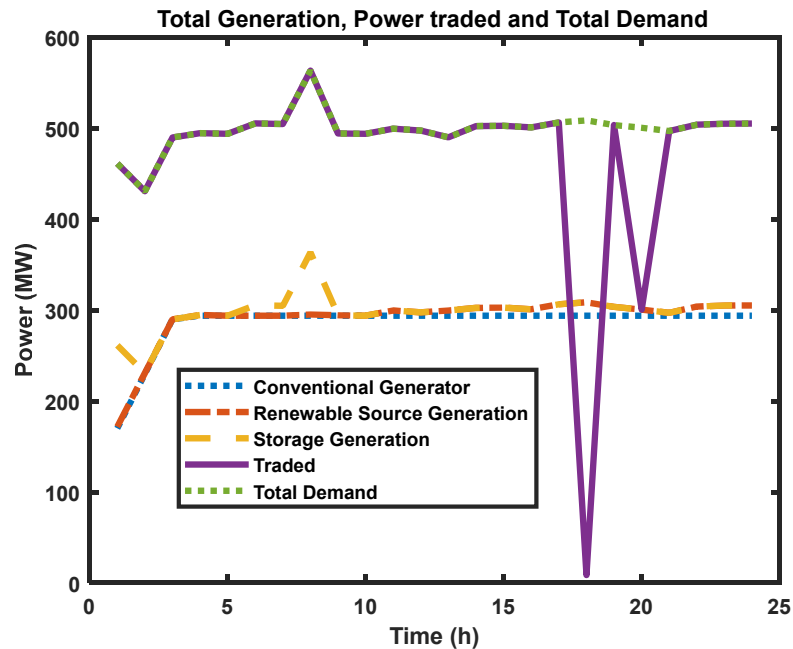


Figure 6-14 Total Generation, Power traded and Total Demand, Comprehensive Control, Fixed Demand

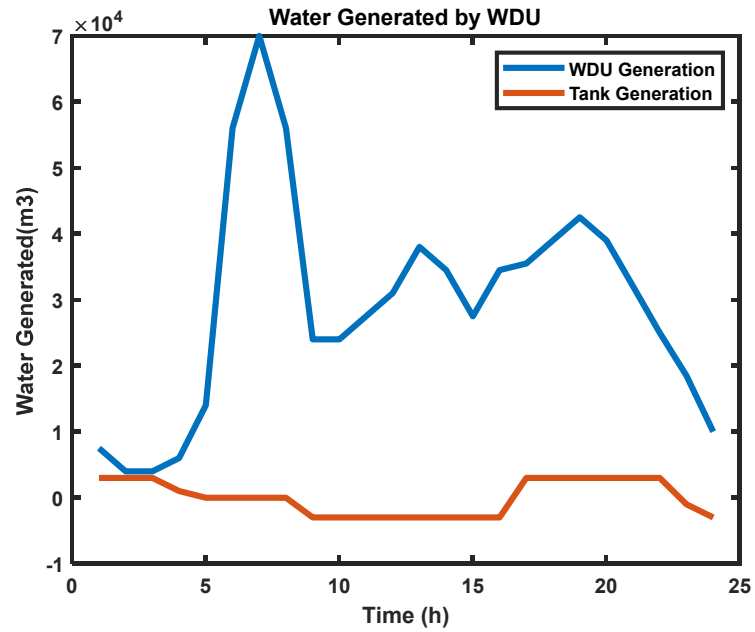


Figure 6-15 Water Generated by WDU, Comprehensive Control, Fixed Demand

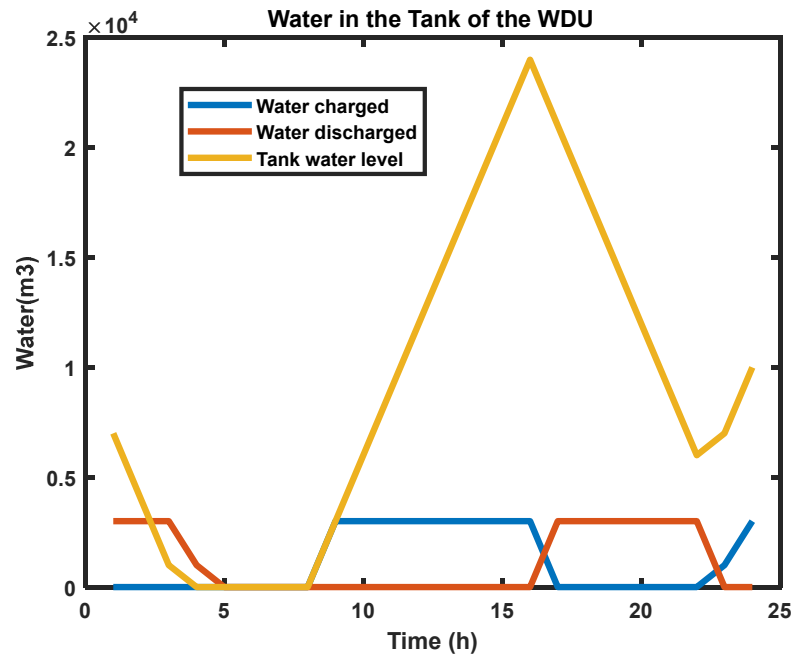


Figure 6-16 Water in the Tank of the WDU, Comprehensive Control, Fixed Demand

6.8.3 Centralized Control, Flexible Demand

In this section, the centralized control scheme with flexible demand is shown for the scaled up WDU, referred to as the third scenario. Figure 6-17 shows that the demand is matching the generation at all points except the 18th hour which is the same as the original system. Figure 6-18 and Figure 6-19 show the water generated by the WDU and its tank in addition to the tank water level and its charge and discharge rates respectively. The figures are very similar to the first scenario. A comparison of the four scenarios will be made in section 6.8.5. An additional figure is shown here which is the water demand. This is because in this case the water demand is flexible and thus, it becomes a variable as shown on Figure 6-20. It can however be seen that the optimization problem has chosen to go with the minimum water load profile at all points except the first one where it has chosen to go with the maximum limit.

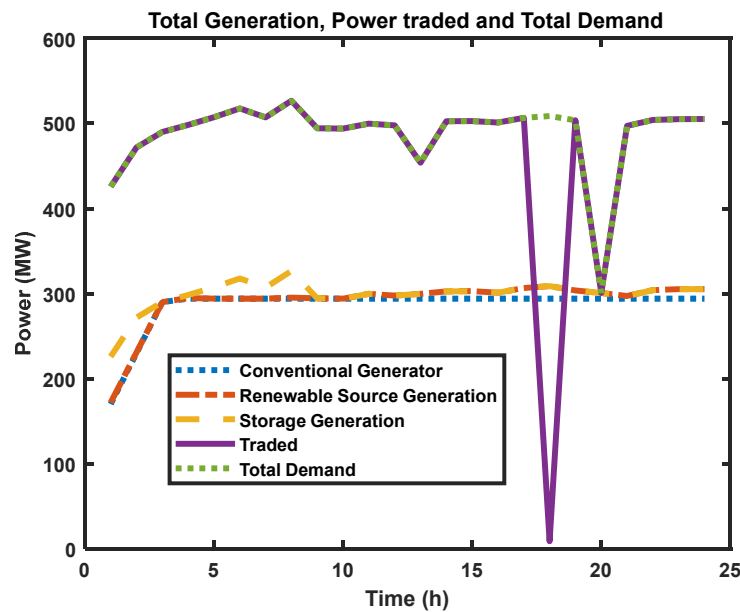


Figure 6-17 Total Generation, Power traded and Total Demand, Centralized Control, Flexible Demand

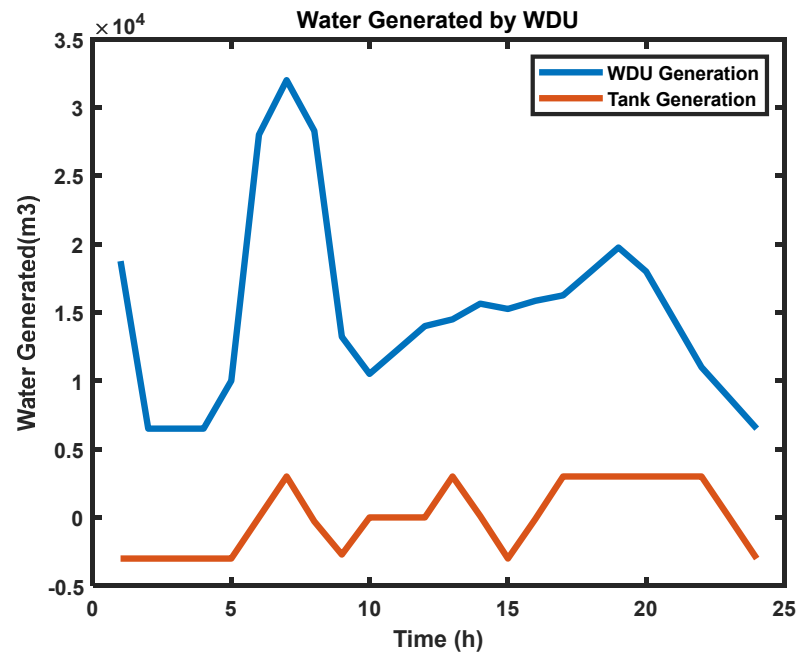


Figure 6-18 Water Generated by WDU, Centralized Control, Flexible Demand

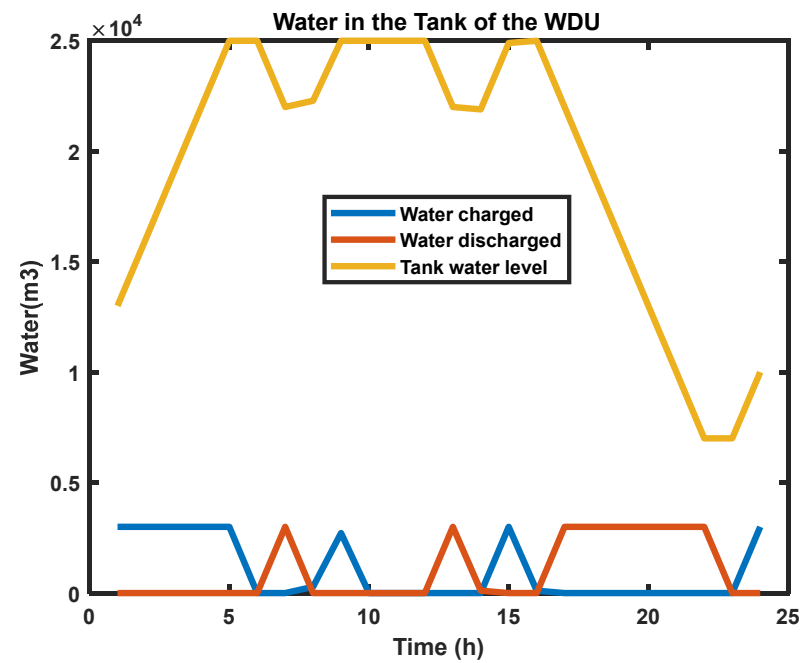


Figure 6-19 Water in the Tank of the WDU, Centralized Control, Flexible Demand

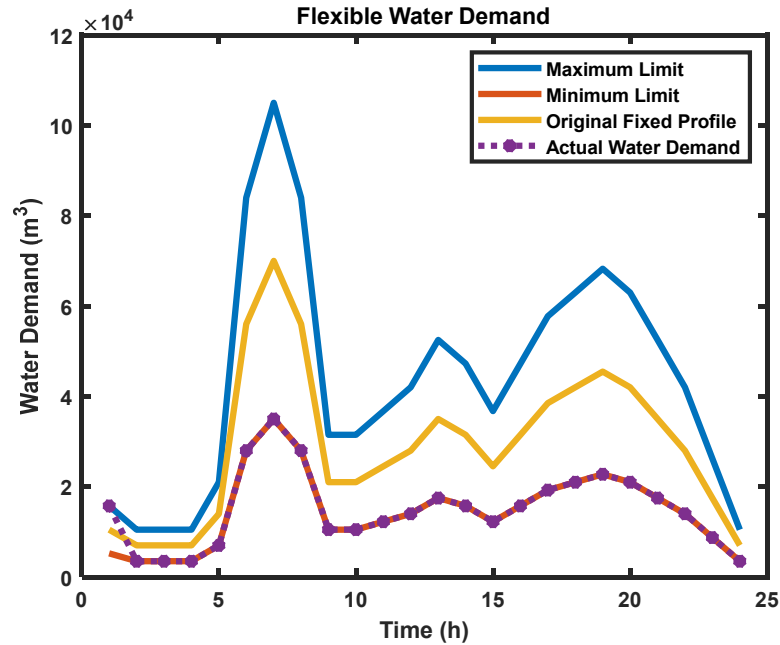


Figure 6-20 Flexible Water Demand, Centralized Control

6.8.4 Comprehensive Control, Flexible Demand

In this fourth and last scenario, the comprehensive control scheme with flexible demand is shown for the scaled up WDU. Figure 6-21 shows that the demand is matching the generation at all points except the 18th hour which is similar to the original system. Figure 6-22 and Figure 6-23 show the water generated by the WDU and its tank in addition to the tank water level and its charge and discharge rates respectively. The figures are very similar to the second scenario. A comparison of the four scenarios will be made in section 6.8.5. Since water demand is also flexible in this scenario, it is shown on Figure 6-24. It can however be seen that the optimization problem has chosen to go with the minimum water load profile at all points.

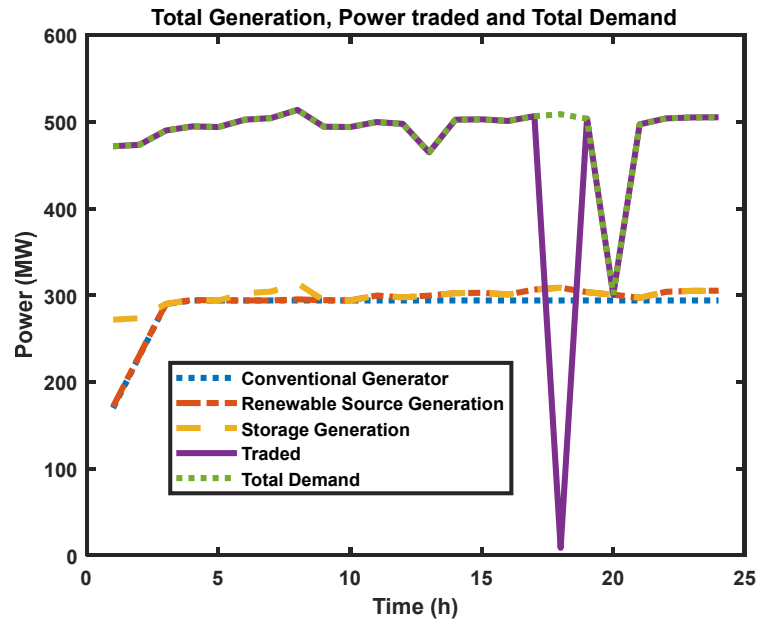


Figure 6-21 Total Generation, Power traded and Total Demand, Comprehensive Control, Flexible Demand

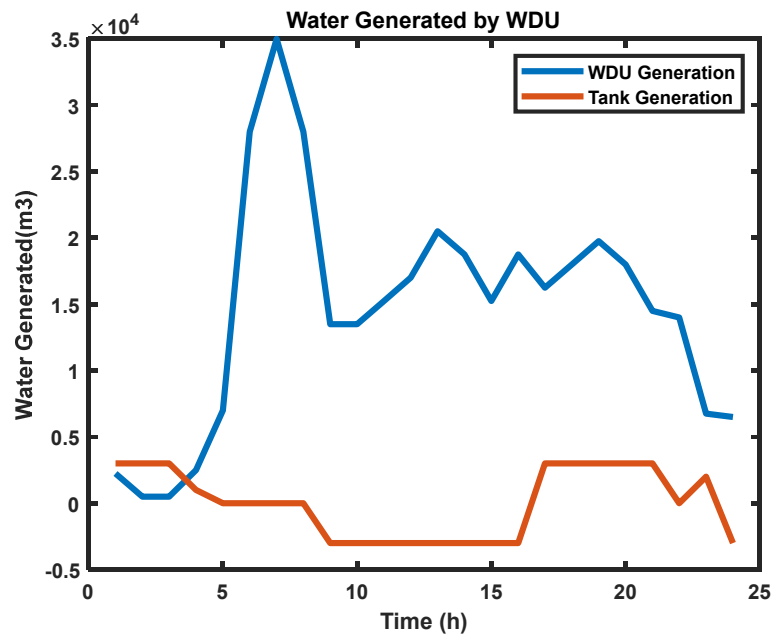


Figure 6-22 Water Generated by WDU, Comprehensive Control, Flexible Demand

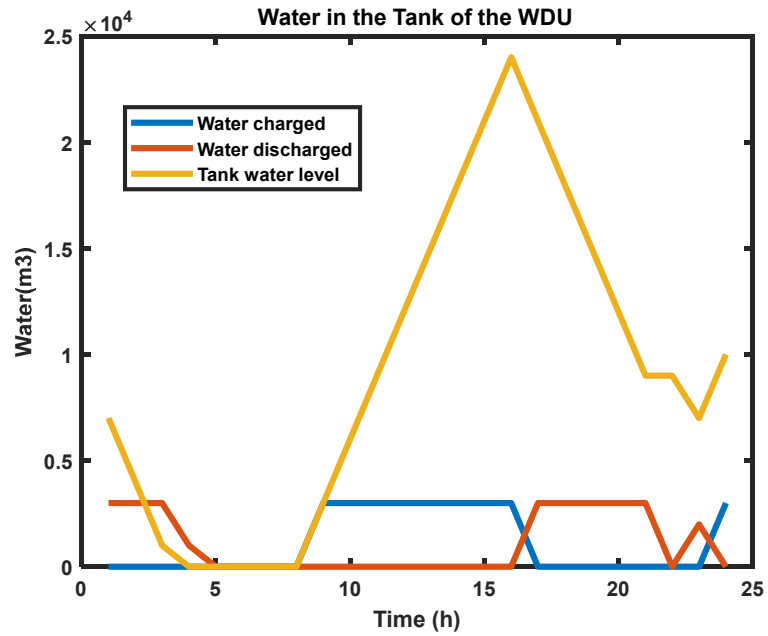


Figure 6-23 Water in the Tank of the WDU, Comprehensive Control, Flexible Demand

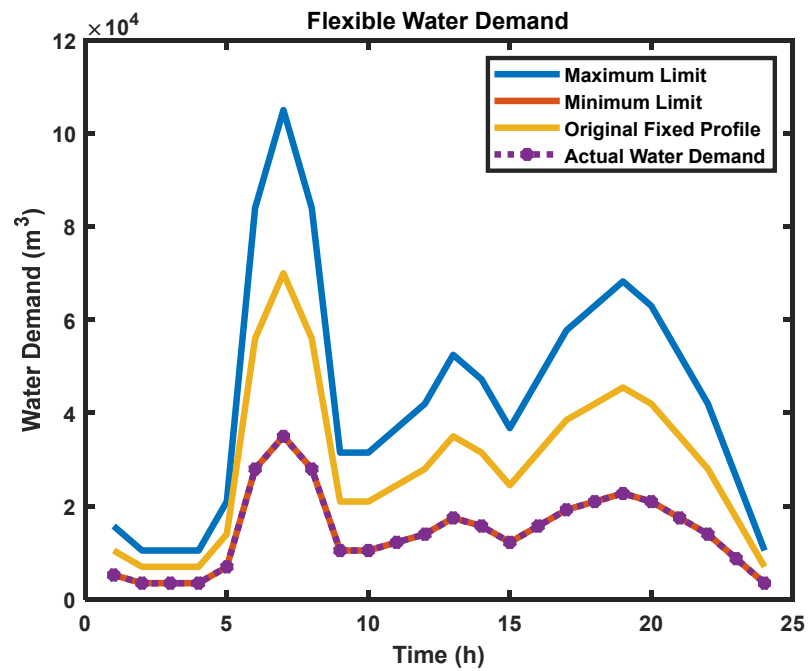


Figure 6-24 Flexible Water Demand, Comprehensive Control

6.8.5 Comparison of Four WDU Scenarios

By comparing the four aforementioned scenarios together in terms of WDU utility, VPP total profit, and WDU energy consumption, the following can be concluded:

1. The energy consumption of the fixed profiles is the same while the flexible profiles have energy consumption at or almost at the minimum load profile.
2. The WDU utility for the fixed profile scenarios is almost the same since the load profile is uncontrolled. However, the utility of the second scenario is a bit lower than the first one which is expected as in the comprehensive control scenario, the WDU tries to minimize its expenses by paying less utility.
3. The WDU utility of the third and fourth scenarios are however much less compared to the first two scenarios. This is because those two scenarios are at the minimum load profile. Also, the fourth scenario of comprehensive control pays lower utility compared to the third scenario as expected.
4. In terms of total VPP profit, in the first two scenarios, the profit is almost the same since the WDU utility is almost the same and the WDU energy consumption is exactly the same. However, in the comprehensive scenario, the second, the total profit is slightly reduced since the WDU pays less utility.
5. In terms of total VPP profit, in the last two scenarios, the profit is almost the same since the WDU utility is almost the same and the WDU energy consumption is almost the same. However, in the comprehensive scenario, the fourth, the total profit is slightly higher though the WDU pays less utility.

The major observation that requires more analysis is: why in the flexible demand scenarios, the system selected the minimum water load profile? The issue can be explained by looking at the hours of failure at each scenario. It will be noticed that in the third and fourth scenarios, the failure happened only at the 18th hour. Thus, though the profit was expected to be higher in the third and fourth scenarios, it was lower for the sake of system power balance. The VPP has chosen to become more reliable than making higher profit.

Table 6-9 WDU utility, profit and energy (comprehensive and centralized control), four scenarios

	WDU Utility (\$)	Total VPP Profit (\$)	WDU Energy (MWh)
First Scenario	78,826.1	365,730.9	1,540.0
Second Scenario	78,276.3	365,729.7	1,540.0
Third Scenario	40,732.2	356,760.1	793.1
Fourth Scenario	38,947.4	356,838.3	770.0

Figure 6-25 shows the hourly utility of the WDU in the four scenarios. It can be seen that the two scenarios of fixed water load profile have similar curves while the two scenarios of flexible water load profile have similar curves as well but different from the first two scenarios. The first five hours on the figure, for the four scenarios, have a different behavior. The fourth scenario, comprehensive control with flexible load, pays the lowest utility over the first five hours. After that, the second scenario, comprehensive control with fixed load, pays the second lowest utility over the first five hours. Then, the third scenario, centralized control with flexible load, pays the third lowest utility over the first five hours. Lastly, the first scenario, centralized control with fixed load, pays the highest utility over the first five hours. This means that whenever a choice is possible in terms of water load flexibility and the WDU having the opportunity to optimize its own objective, the WDU chooses to go with paying the lowest utility over the first five hours; while load flexibility

allows for more utility reduction compared to the comprehensive control scheme. This shows the effective utilization of the water tank of the WDU with the availability of flexibility.

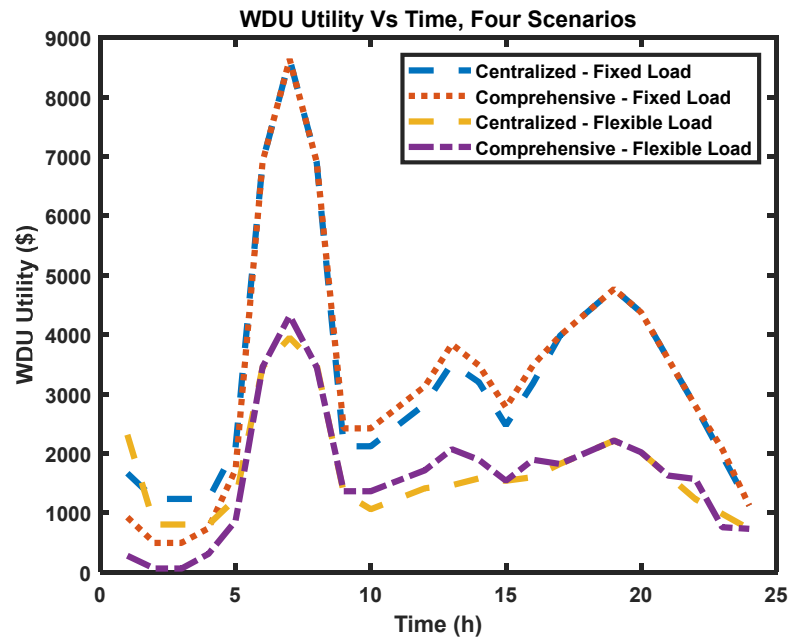


Figure 6-25 WDU Utility Vs Time, Four Scenarios

A very important aspect of considering a WDU is the utilization of the water tank as a virtual storage for the electrical system. The third scenario where the load is flexible and the control scheme is centralized will be evaluated for this purpose. By looking at Figure 6-26, it can be seen that the figure has three segments. In the first segment, the utility the WDU will pay to the VPP is higher than the RT market price. Thus, it is more beneficial for the VPP to sell electric power to the WDU instead of the network. This is why the water tank is charging during the first segment on the figure at all hours except the 7th hour where the tank discharges water. At the 7th hour specifically, the RT market price increased by a good margin which is why the tank started discharging at that hour only. The second

segment on the figure has a similar behavior to the first segment and a similar analysis. However, at the 13th hour, the RT market price is higher than the WDU utility which encourages the water tank to discharge as shown. The third and last segment on the figure shows a different behavior. It can be seen that the tank is discharging water almost at all hours in the third segment though the WDU utility price is higher than the RT market price. This is because there is a minimum water demand level that has to be satisfied. Therefore, the tank was forcefully discharging water at the third segment in order to fulfill the minimum daily water demand level. Nonetheless, the tank could have switched its behavior between the first and third segments as they both have a similar trend.

The reason why the tank selected to discharge water for demand satisfaction in the third segment instead of the first is that the price difference between the WDU utility price and the RT market price in the third segment is lower than that of the first segment. Therefore, it is more profitable to discharge in the third segment of the figure where the price difference is lower.

Lastly, some hours especially at the end of every segment do not necessarily follow the trend of that segment. This is because the analysis is not limited to the RT market price and the WDU utility price only. The analysis should take into account the utility of all demands at all buses as well. As the decision of selling and buying is controlled by the utility of the electrical demands too. Nonetheless, the utilization of the water tank of the WDU as a virtual storage for the electrical system optimization has been proven. Thus, the consideration of a WDU as part of the VPP is essential for the utilization of the water tanks

as storage mediums in addition to the high importance of water desalination for countries that rely heavily of desalination as a main source for sweet water.

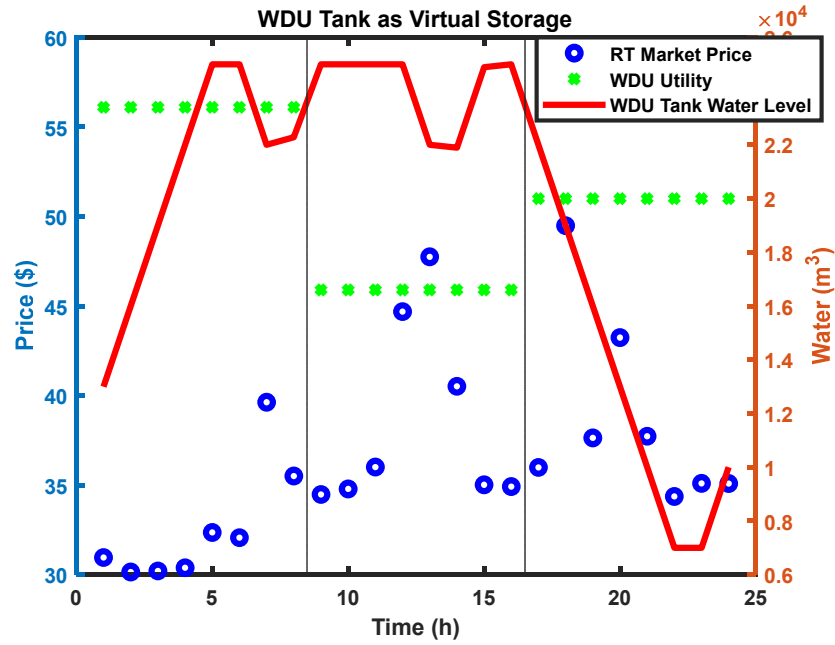


Figure 6-26 WDU Tank as Virtual Storage

6.9 Number of Scenarios Vs Reliability Objective

In the previous section, the system was simulated after incorporating a WDU, and the proposed reliability objective. That was however done for the case where there are 125 scenarios divided to five wind power scenarios, five DA market price scenarios, and five RT market price scenarios. Increasing the number of scenarios could solve the problem of having multiple failures to participate into the RT market. This is because considering more scenarios means that some of the newly introduced scenarios could help eliminating this high failure rate. Therefore, more scenarios will be considered without the reliability constraints and the results will be compared to those of the previous section.

First, 50 scenarios were considered for each uncertain parameter which means having a total of $50 \times 50 \times 50$ scenarios, i.e., 125,000 scenarios. This simulation failed due to the considerable amount of computer memory required for such simulation. It is worth noting that this simulation was run on a computer with a 32 GB memory. The number of scenarios was reduced to 20 for each uncertain parameter which gives a total of 8,000 scenarios but this has also failed due to the need for bigger memory. Therefore, the first outcome in the test of the case of increase of the number of scenarios is that it is computationally costly. The number of scenarios was reduced to ten for each uncertain parameter resulting in a total of 1,000 scenarios which was manageable with the available memory.

Table 6-10 Power Exchange - 1000 scenarios

	With Reliability	1000 Scenarios	With Reliability	1000 Scenarios	With Reliability	1000 Scenarios	With Reliability	1000 Scenarios
	Total Generation (MW)	Total Generation (MW)	Demand (MW)	Demand (MW)	DA Power (MW)	DA Power (MW)	RT Power (MW)	RT Power (MW)
t1	271.83	271.83	471.83	471.83	-200.00	-200.00	0.00	0.00
t2	300.41	299.31	500.41	499.31	-200.00	-200.00	0.00	0.00
t3	292.90	290.00	492.90	490.00	-200.00	-200.00	0.00	0.00
t4	294.69	294.69	494.69	494.69	-200.00	-200.00	0.00	0.00
t5	301.54	303.62	501.54	503.62	-200.00	-200.00	0.00	0.00
t6	294.00	295.03	494.00	495.03	-200.00	0.00	0.00	-200.00
t7	294.00	294.89	494.00	494.89	0.00	0.00	-200.00	-200.00
t8	295.25	295.25	495.25	495.25	0.00	-200.00	-200.00	0.00
t9	294.36	294.36	494.36	494.36	-200.00	-200.00	0.00	0.00
t10	294.00	294.00	494.00	494.00	-200.00	-200.00	0.00	0.00

	With Reliability	1000 Scenarios	With Reliability	1000 Scenarios	With Reliability	1000 Scenarios	With Reliability	1000 Scenarios
	Total Generation (MW)	Total Generation (MW)	Demand (MW)	Demand (MW)	DA Power (MW)	DA Power (MW)	RT Power (MW)	RT Power (MW)
t11	299.71	299.71	499.71	499.71	-200.00	-17.18	0.00	-182.82
t12	297.62	297.62	497.62	497.62	-200.00	300.00	0.00	0.00
t13	299.65	299.65	426.35	499.65	0.00	300.00	-126.70	-500.00
t14	302.52	302.52	502.52	502.52	300.00	300.00	-500.00	-500.00
t15	302.84	302.84	502.84	502.84	-200.00	300.00	0.00	-500.00
t16	301.01	301.01	501.01	501.01	300.00	300.00	-500.00	-500.00
t17	306.51	306.51	506.51	506.51	300.00	300.00	-500.00	-500.00
t18	308.74	308.74	508.74	508.74	300.00	300.00	0.00	0.00
t19	303.64	303.64	503.64	503.64	300.00	300.00	-500.00	-500.00
t20	300.67	300.67	300.67	500.67	0.00	-200.00	0.00	0.00
t21	297.11	297.11	497.11	497.11	0.00	0.00	-200.00	-200.00
t22	304.03	304.03	504.03	504.03	300.00	300.00	-500.00	-500.00
t23	305.10	305.10	505.10	505.10	-200.00	-200.00	0.00	0.00
t24	305.26	305.26	505.26	305.26	-200.00	0.00	0.00	0.00

Table 6-11 Hourly net profit without DA market revenue - 1000 scenarios

Hour	Net profit (\$) with Reliability	Net profit (\$) with 1000 scenarios
h1	25,277.52	25,277.07
h2	25,924.64	25,862.93
h3	22,786.22	22,623.50
h4	22,700.68	22,700.68
h5	23,084.89	23,201.61
h6	22,661.90	16,305.49
h7	14,735.90	14,786.02
h8	15,629.94	22,731.94
h9	17,456.81	17,432.64
h10	17,680.78	17,694.90
h11	17,971.99	11,386.88
h12	17,858.48	17,801.84
h13	8,327.53	-5,919.37
h14	-2,211.51	-2,187.76
h15	18,023.67	570.17
h16	488.92	488.92
h17	3,698.62	3,698.62
h18	21,814.75	21,810.35
h19	2,711.00	2,711.00
h20	9,555.84	21,370.77
h21	13,634.29	13,635.21
h22	4,412.94	4,413.86
h23	21,663.52	21,666.09
h24	21,697.65	10,212.21

Table 6-12 Hourly net profit without DA market revenue - 1000 scenarios

Utility and RT Profit (\$) with Reliability	Utility and RT Profit (\$) 1000 scenarios	DA Market Net Profit (\$) with Reliability	DA Market Net Profit (\$) 1000 scenarios	Net profit (\$) with Reliability	Net profit (\$) 1000 scenarios	Net profit (\$) original case
367,586.97	330,275.58	-8,631	56,348.23	358,955.97	386,623.81	427,528.82

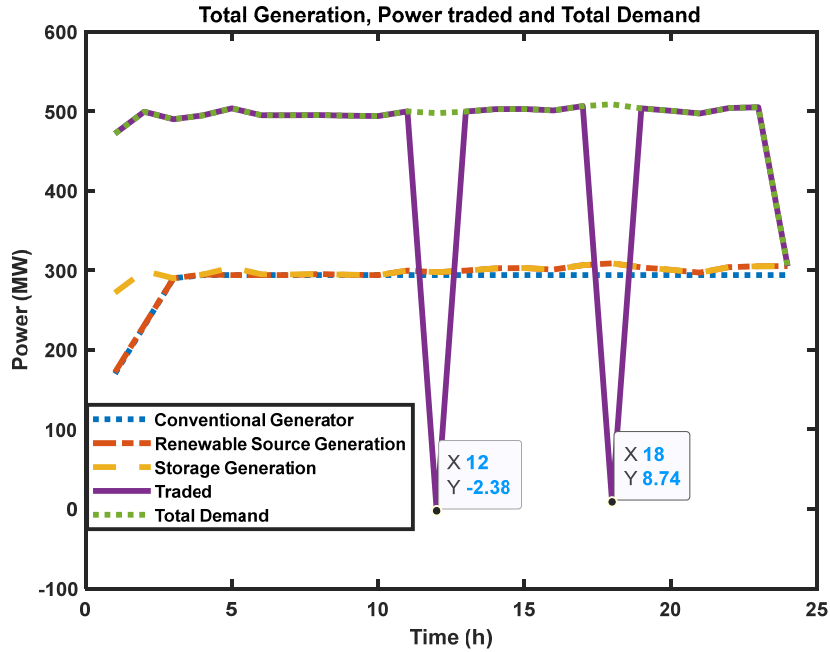


Figure 6-27 Total generation, power traded and demand – 1000 scenarios

Table 6-13 Time Elapsed – Reliability Vs 1000 Scenarios

Time Elapsed, DA, with Reliability (S)	Time Elapsed, DA, 1000 scenarios (S)	Time Elapsed, RT, with Reliability (S)	Time Elapsed, RT, 1000 scenarios (S)
74	847	175	789

It can be noticed that increasing the number of scenarios has solved the failure at the 20th and the 23rd hour while the reliability constraints have solved the failure at 3 hours (12th, 20th, and the 23rd). Therefore, saving two failures has dropped the net profit from 427,528.82\$ to 386,623.81\$ by increasing the number of scenarios. In the case of considering the reliability constraints, three failures were avoided and the profit dropped from 427,528.82\$ to 358,955.97\$. Thus, it can be concluded that the profit drop is relative to the number of failures avoided. Nevertheless, the reliability constraints model was more effective avoiding failures.

In terms of time consumed, the DA market simulation for the case with reliability constraints has taken less than 9% of the time consumed for the case with 1000 scenarios. For the RT market simulation, the time consumed for the reliability constraints model was only around 22% of the time consumed for the 1000 scenarios model. Thus, the proposed model with reliability constraints is more effective at eliminating the failures, considerably faster in terms of simulation time, and affects the profit almost the same way as the other model.

6.10 VPP Cluster Base Design

In this section, a simple VPP cluster with only one VPP connected to an EP is designed and simulated. After applying the proposed and designed model as explained on the previous sections, the VPP cluster is simulated and compared to the original VPP that was simulated without having EP involved. First, the DA results will be unchanged since the DA market scheduling is still a stage before the dispatch level. When it comes to the RT market, the original VPP failed to dispatch at four hours: the 12th, 18th, 20th, and 23rd hours. Then, with the introduction of the reliability constraints, the failure happened only at the 18th hour. It is expected that after the involvement of an EP, that hour of failure to meet the demand shall be eliminated. This of course will vary based on the size of the VPP and the EP. The size of the EP considered in this case 1000 MWh. The details of the added EP are presented on Table 6-14. It must be noted that the data of the EP as a source shall exactly match the data of the EP when acting as a load. It can be seen from Table 6-15 and Table

6-16 that the load ramp up and the load ramp down are matching the charging and discharging rates of the EP when acting as a storage. Also, it has a minimum of zero demand to avoid disturbing the balance of VPP when acting as a load. But to ensure that the VPP will pay back the energy it has taken, the utility of the EP when acting as a load is set to a high value. This will encourage the VPP to feed the EP before other loads due to its fake high utility value without having to disturb the balance of the VPP by setting the EP minimum values to zero.

Table 6-14 EP source data

Capacity	1000 MWh
Initial Energy	1000 MWh
Charging/ discharging efficiency	90%/90%
Maximum charge power	500 MW
Maximum discharge power	500 MW

Table 6-15 EP load data

Demand	$\underline{E}_d^D$ [MWh]	$\bar{P}_{dt}^D$ [MW]	$R_a^{D,U}$ $\left[\frac{\text{MW}}{\text{h}}\right]$	$-R_a^{D,D}$ $\left[\frac{\text{MW}}{\text{h}}\right]$	p_{do}^D [MW]
EP	0	$p^{from,EP}$	500	500	0

Table 6-16 EP load data 2

Time	$\underline{P}_{1t}^D$	Utility
h	[MW]	\$
All	0	100

Based on those details, the simulation results are presented and compared to the original VPP simulation that was presented in section 6.6.

Table 6-17 VPP VS cluster VPP RT power

Hour	Original VPP Power (MW)	VPP Cluster Power (MW)
t1	0.00	0.00
t2	0.00	0.00
t3	0.00	0.00
t4	0.00	0.00
t5	0.00	0.00
t6	0.00	0.00
t7	-200.00	-200.00
t8	-200.00	-200.00
t9	0.00	0.00
t10	0.00	0.00
t11	0.00	0.00
t12	0.00	0.00
t13	-126.70	-126.70
t14	-500.00	-500.00
t15	0.00	0.00
t16	-500.00	-500.00
t17	-500.00	-500.00
t18	0.00	0.00
t19	-500.00	-500.00
t20	0.00	0.00
t21	-200.00	-200.00
t22	-500.00	-500.00
t23	0.00	0.00
t24	0.00	0.00

Table 6-18 VPP VS cluster VPP profit

Hour	Original VPP Revenue (\$)	Profit (utility – generator cost) (\$)	Net profit (\$)	VPP Cluster Revenue (\$)	Profit (utility – generator cost) (\$)	Net profit (\$)
t1	0	25,277.52	25,277.52	0.00	25,277.52	25,277.52
t2	0	25,924.64	25,924.64	0.00	25,924.64	25,924.64
t3	0	22,786.22	22,786.22	0.00	22,786.22	22,786.22
t4	0	22,700.68	22,700.68	0.00	22,700.68	22,700.68
t5	0	23,084.89	23,084.89	0.00	23,084.89	23,084.89

Hour	Original VPP Revenue (\$)	Profit (utility – generator cost) (\$)	Net profit (\$)	VPP Cluster Revenue (\$)	Profit (utility – generator cost) (\$)	Net profit (\$)
t6	0	22,661.90	22,661.90	0.00	22,661.90	22,661.90
t7	-7,926.00	22,661.90	14,735.90	-7,926.00	22,661.90	14,735.90
t8	-7,102.00	22,731.94	15,629.94	-7,102.00	22,731.94	15,629.94
t9	0	17,456.81	17,456.81	0.00	17,456.81	17,456.81
t10	0	17,680.78	17,680.78	0.00	17,679.93	17,679.93
t11	0	17,971.99	17,971.99	0.00	17,966.91	17,966.91
t12	0	17,858.48	17,858.48	0.00	17,864.54	17,864.54
t13	-6,050.16	14,377.69	8,327.53	-6,050.16	14,377.69	8,327.53
t14	-20,260.00	18,048.49	-2,211.51	-20,260.00	18,035.86	-2,224.14
t15	0	18,023.67	18,023.67	0.00	18,036.17	18,036.17
t16	-17,460.00	17,948.92	488.92	-17,460.00	17,948.92	488.92
t17	-17,995.00	21,693.62	3,698.62	-17,995.00	21,693.62	3,698.62
t18	0	21,814.75	21,814.75	0.00	21,814.75	21,814.75
t19	-18,820.00	21,531.00	2,711.00	-18,820.00	5,902.71	-12,917.29
t20	0	9,555.84	9,555.84	0.00	410.34	410.34
t21	-7,546.00	21,180.29	13,634.29	-7,546.00	8,329.08	783.08
t22	-17,185.00	21,597.94	4,412.94	-17,185.00	21,524.56	4,339.56
t23	0	21,663.52	21,663.52	0.00	21,666.67	21,666.67
t24	0	21,697.65	21,697.65	0.00	21,697.65	21,697.65

It can be seen from the tables above that the simulation results are generally the same. The storage and renewable energy source of the VPP are also having the same results for both the original VPP and the VPP cluster. It can be noticed however in terms of profit that the major differences start after and slightly at the 18th hour. This is actually because the original VPP fails to meet its demand at the 18th hour and thus, the EP will supply the VPP with power at the 18th hour and it will have to start returning that power back from the 19th hour. It can be seen that the major difference in profit happens after 18th hours which is the hour of failure of the original VPP. Therefore, the VPP cluster has been designed and it has operated successfully. Nonetheless, this does not yet cover the interaction between the EP and the VPP. This only shows the effect on the interaction between the VPP and the market.

Table 6-19 shows the result and the interaction between the EP and the VPP inside the VPP cluster.

Table 6-19 EP and VPP interaction

	Power with EP (MW)	$\lambda^{RT,act}$ (\$/MWh)
t1	0.00	0.00
t2	0.00	0.00
t3	0.00	0.00
t4	0.00	0.00
t5	0.00	0.00
t6	0.00	0.00
t7	0.00	0.00
t8	0.00	0.00
t9	0.00	0.00
t10	0.00	0.00
t11	0.00	0.00
t12	0.00	0.00
t13	0.00	0.00
t14	0.00	0.00
t15	0.00	0.00
t16	0.00	0.00
t17	0.00	0.00
t18	617.28	49.49
t19	-257.98	37.64
t20	-143.53	43.24
t21	-215.78	37.73
t22	0.00	0.00
t23	0.00	0.00
t24	0.00	0.00

As confirmed by the previous results, it can be seen on Table 6-19 that at the 18th hour, the VPP starts taking power from the EP. During the 19th to the 21st hour, the VPP continues to pay back the power taken on the 18th hour. Note that each time a transaction is done, the market price is noted as it will affect the overall profit of the VPP but it will not affect the EP in terms of profit as the EP's main purpose is power balance. On the 18th hour, the VPP

fails to meet its demand and it drains the maximum discharge rate of the EP which is 500 MW/h. However, due to the efficiency considered of 90%, the 10% loss is loaded onto the VPP as power that has been taken by the VPP. Another 10% is considered as the EP recharge efficiency is 90% as well. Therefore, it is noted on the table as $500/0.9/0.9$ which is 617.28. The power returned back by the VPP to the EP is not multiplied by 0.9 for efficiency considerations as this has already been considered when divided by 0.9 twice, once for the charging efficiency and once for the discharging efficiency. By the end of the trading day, the VPP owes the EP 0 MW which means that the VPP has settled all its power due to the EP. Additionally, the interaction of the VPP with the EP will have a financial impact onto the profit of the virtual power plant as per (6-2). This effect is -24,057.76 \$. The overall profit comparison is shown on Table 6-20. It is clear that there is a drop in profit, but it is expected that the VPP operator would have lost/paid more to cover the hour/s of mismatch if it was not for the presence of the EP. It can be seen that the loss in profit is -37,695.25 \$. This is different from the calculation above. This is due to the fact that the loss is not happening only when the power is supplied back to the EP. It is happening also in terms of the demand that could not be supplied. In other words, the loss of the utility also impacts the overall reduction in profit.

Table 6-20 Hourly net profit without DA market revenue

Original VPP Utility and RT Profit	Original VPP DA Market Net Profit	Original VPP Net profit (\$)	VPP cluster Utility and RT Profit	VPP cluster DA Market Net Profit	VPP cluster Net profit (\$)
367,586.97	-8,631	358,955.97	329,891.72	-8,631	321,260.72

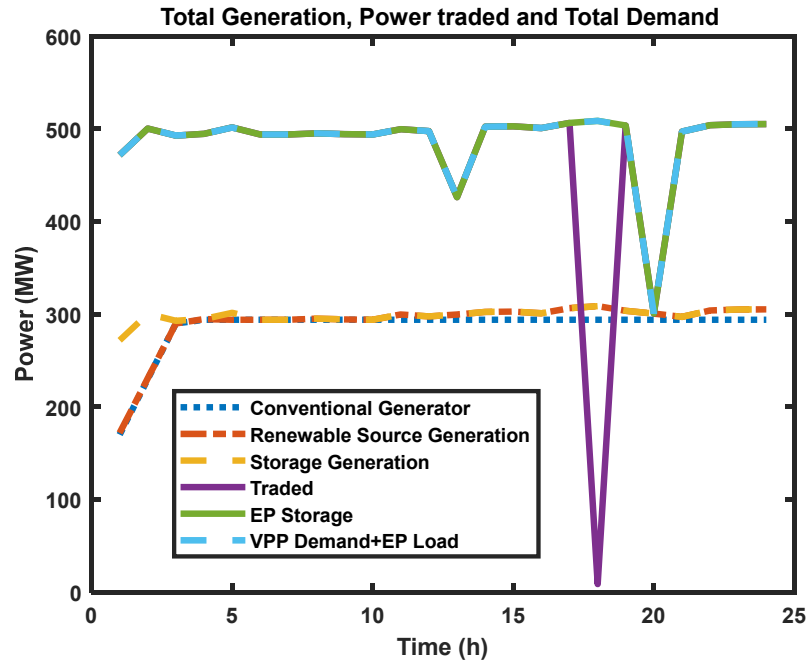


Figure 6-28 Total generation, power traded and demand of VPP cluster – Base design

Lastly, Figure 6-28 shows the demand and generation balance of the VPP cluster which can be compared to the same figure of the original VPP on Figure 6-5. The original VPP had power mismatch between supply and demand at the 18th hour. However, the VPP cluster did not suffer from this issue at all. Therefore, the EP has successfully achieved its task.

CHAPTER 7

VPP Cluster Simulation

7.1 VPP Cluster DA Model

Based on the analysis and the studies presented earlier, the equations governing the DA market simulation have been selected as follows:

$$\max_{\Phi^{DA,S}} \sum_{\omega \in \Pi^{DA}} \sum_{\gamma \in \Pi^{RT}} \pi_{\omega\gamma} \zeta_{\omega\gamma} + \beta \left[\rho - \frac{1}{1-\alpha} \sum_{\omega \in \Pi^{DA}} \sum_{\gamma \in \Pi^{RT}} \pi_{\omega\gamma} \mu_{\omega\gamma} \right] \quad (7-1)$$

$$\begin{aligned} \zeta_{\omega\gamma} = \sum_{t \in \Omega^T} \left[\lambda_{t\omega\gamma}^{DA} p_{t\omega}^{DA} \Delta t + (\lambda_{t\omega\gamma}^{DA} + r_{t\omega\gamma}^{RT}) p_{t\omega\gamma}^{RT} \Delta t + \sum_{d \in \Omega^D} U_{dt}^D p_{dt\omega\gamma}^D \Delta t \right. \\ \left. - \sum_{w \in \Omega^{WDU}} U_{wt}^{WDU} p_{wt\omega\gamma}^{WDU} \Delta t - \sum_{c \in \Omega^C} (C_{ct\omega\gamma}^C \Delta t + \bar{c}_{ct\omega\gamma}^C \right. \\ \left. + \underline{c}_{ct\omega\gamma}^C) \right], \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \end{aligned} \quad (7-2)$$

$$-\zeta_{\omega\gamma} + \rho - \mu_{\omega\gamma} \leq 0, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-3)$$

$$0 \leq \mu_{\omega\gamma}, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-4)$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega_n^D} p_{st\omega\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\omega\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\omega\gamma}^L \\
& = p_{nt\omega\gamma}^M + \sum_{d \in \Omega_n^D} p_{dt\omega\gamma}^D + \sum_{w \in \Omega_n^{WDU}} p_{wt\omega\gamma}^{WDU}, \forall n \in \Omega^M, \forall t \\
& \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT}
\end{aligned} \tag{7-5}$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\omega\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\omega\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\omega\gamma}^L \\
& = \sum_{d \in \Omega_n^D} p_{dt\omega\gamma}^D + \sum_{w \in \Omega_n^{WDU}} p_{wt\omega\gamma}^{WDU}, \forall n \in \Omega^N \setminus n \in \Omega^M, \forall t \\
& \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT}
\end{aligned} \tag{7-6}$$

$$p_{t\omega}^{DA} + p_{t\omega\gamma}^{RT} = \sum_{n \in \Omega^M} p_{nt\omega\gamma}^M, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \tag{7-7}$$

$$\begin{aligned}
p_{\ell t\omega\gamma}^L & = B_\ell(\delta_{s(\ell)t\omega\gamma} - \delta_{r(\ell)t\omega\gamma}), \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega \\
& \in \Pi^{DA}, \forall \gamma \Pi^{RT}
\end{aligned} \tag{7-8}$$

$$-\bar{P}_\ell^L \leq p_{\ell t\omega\gamma}^L \leq \bar{P}_\ell^L, \forall \ell \in \Omega^L, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \tag{7-9}$$

$$\delta_{nt\omega\gamma} = 0, n: \text{ref.}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \tag{7-10}$$

$$-\pi \leq \delta_{nt\omega\gamma} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \tag{7-11}$$

$$\underline{P}^V \leq p_{t\omega}^{\text{DA}} \leq \bar{P}^V, \forall t \in \Omega^T \quad (7-12)$$

$$\underline{P}^V \leq p_{t\omega}^{\text{DA}} + p_{t\omega\gamma}^{\text{RT}} \leq \bar{P}^V, \forall t \in \Omega^T, \forall \omega, \forall \gamma \Pi^{\text{RT}} \quad (7-13)$$

$$-\bar{P}_n^{\text{M}} \leq p_{nt\omega\gamma}^{\text{M}} \leq \bar{P}_n^{\text{M}}, \forall n \in \Omega^{\text{M}}, \forall t \in \Omega^{\text{D}}, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \quad (7-14)$$

$$\sum_{t \in \Omega^T} p_{dt\omega\gamma}^{\text{D}} \Delta t \geq \underline{E}_d^{\text{D}}, \forall d \in \Omega^{\text{D}}, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \quad (7-15)$$

$$\underline{P}_{dt}^{\text{D}} \leq p_{dt\omega\gamma}^{\text{D}} \leq \bar{P}_{dt}^{\text{D}}, \forall d \in \Omega^{\text{D}}, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \quad (7-16)$$

$$\begin{aligned} -R_d^{\text{D,D}} \Delta t \leq p_{dt\omega\gamma}^{\text{D}} - p_{d(t-1)\omega\gamma}^{\text{D}} \leq R_d^{\text{D,U}} \Delta t, \forall d \in \Omega^{\text{D}}, \forall t \in \Omega^T, \forall \omega \\ \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \end{aligned} \quad (7-17)$$

$$\underline{P}_c^{\text{C}} u_{ct\omega\gamma}^{\text{C}} \leq p_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \quad (7-18)$$

$$p_{ct\omega\gamma}^{\text{C}} \leq p_{ct\omega\gamma}^{\text{C,max}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \quad (7-19)$$

$$p_{ct\omega\gamma}^{\text{C,max}} \leq \bar{P}_c^{\text{C}} u_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^T, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \Pi^{\text{RT}} \quad (7-20)$$

$$\begin{aligned}
p_{ct\omega\gamma}^{\text{C,max}} - p_{c(t-1)\omega\gamma}^{\text{C}} & \\
&\leq R_c^{\text{C,U}} * \Delta t * u_{c(t-1)\omega\gamma}^{\text{C}} + R_c^{\text{C,SU}} * \Delta t \\
&* (u_{ct\omega\gamma}^{\text{C}} - u_{c(t-1)\omega\gamma}^{\text{C}}) + \bar{P}_c^{\text{C}}(1 - u_{ct\omega\gamma}^{\text{C}}), \forall c \in \Omega^{\text{C}}, \forall t \\
&\in \Omega^{\text{T}}, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \in \Pi^{\text{RT}}
\end{aligned} \tag{7-21}$$

$$\begin{aligned}
p_{c(t-1)\omega\gamma}^{\text{C}} - p_{ct\omega\gamma}^{\text{C}} & \\
&\leq R_c^{\text{C,D}} * \Delta t * u_{ct\omega\gamma}^{\text{C}} + R_c^{\text{C,SD}} * \Delta t \\
&* (u_{c(t-1)\omega\gamma}^{\text{C}} - u_{ct\omega\gamma}^{\text{C}}) + \bar{P}_c^{\text{C}}(1 - u_{c(t-1)\omega\gamma}^{\text{C}}), \forall c \\
&\in \Omega^{\text{C}}, \forall t \in \Omega^{\text{T}}, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \in \Pi^{\text{RT}}
\end{aligned} \tag{7-22}$$

$$\begin{aligned}
p_{ct\omega\gamma}^{\text{C,max}} &\leq \bar{P}_c^{\text{C}} * u_{c(t+1)\omega\gamma}^{\text{C}} + R_c^{\text{C,SD}} * \Delta t * (u_{ct\omega\gamma}^{\text{C}} - u_{c(t+1)\omega\gamma}^{\text{C}}), \forall c \\
&\in \Omega^{\text{C}}, \forall (t \leq TT - 1) \in \Omega^{\text{T}}, \forall \omega \in \Pi^{\text{DA}}, \forall \gamma \in \Pi^{\text{RT}}
\end{aligned} \tag{7-23}$$

$$\bar{C}_c^{\text{C}}(u_{ct\omega\gamma}^{\text{C}} - u_{c(t-1)\omega\gamma}^{\text{C}}) \leq \bar{c}_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^{\text{T}}, \forall \omega, \forall \gamma, \tag{7-24}$$

$$0 \leq \bar{c}_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^{\text{T}}, \forall \omega, \forall \gamma, \tag{7-25}$$

$$\underline{C}_c^{\text{C}}(u_{c(t-1)\omega\gamma}^{\text{C}} - u_{ct\omega\gamma}^{\text{C}}) \leq \underline{c}_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^{\text{T}}, \forall \omega, \forall \gamma, \tag{7-26}$$

$$0 \leq \underline{c}_{ct\omega\gamma}^{\text{C}}, \forall c \in \Omega^{\text{C}}, \forall t \in \Omega^{\text{T}}, \forall \omega, \forall \gamma, \tag{7-27}$$

$$e_{st\omega\gamma}^S = e_{s(t-1)\omega\gamma}^S + \eta_s^{S,C} p_{st\omega\gamma}^{S,C} \Delta t - \frac{p_{st\omega\gamma}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega$$

$$\in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (7-28)$$

$$\underline{E}_{st}^S \leq e_{st\omega\gamma}^S \leq \bar{E}_{st}^S, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (7-29)$$

$$0 \leq p_{st\omega\gamma}^{S,C} \leq \bar{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (7-30)$$

$$0 \leq p_{st\omega\gamma}^{S,D} \leq \bar{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (7-31)$$

$$p_{st\omega\gamma}^S = p_{st\omega\gamma}^{S,D} - p_{st\omega\gamma}^{S,C}, \forall s \in \Omega^S, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (7-32)$$

$$0 \leq p_{rt\omega\gamma}^R \leq \bar{P}_{rt\omega\gamma}^{R,A}, \forall r \in \Omega^R, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \Pi^{RT} \quad (7-33)$$

$$p_{t\omega}^{DA} \leq p_{t\omega'}^{DA}, \text{ if } \lambda_{t\omega}^{DA} \leq \lambda_{t\omega'}^{DA}, \forall t \in \Omega^T, \forall \omega, \forall \omega' \quad (7-34)$$

$$p_{t\omega}^{DA} = p_{t\omega'}^{DA}, \text{ if } \lambda_{t\omega}^{DA} = \lambda_{t\omega'}^{DA}, \forall t \in \Omega^T, \forall \omega, \forall \omega' \quad (7-35)$$

$$C_{ct\omega\gamma}^C = C_c^{C,F} * u_{ct\omega\gamma}^C + \sum_{x=1}^{Nx} C_x^V * P_{ct\omega\gamma x}, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega$$

$$\in \Pi^{DA}, \forall \gamma \Pi^{RT}, \quad (7-36)$$

$$p_{ct\omega\gamma}^C = \underline{p}_c^C * u_{ct\omega\gamma}^C + \sum_{x=1}^{Nx} P_{ct\omega\gamma x}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT}, \quad (7-37)$$

$$P_{ct\omega\gamma x} \leq p_x^V - p_{x-1}^V, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT}, \forall x \in [2, Nx - 1] \quad (7-38)$$

$$P_{ct\omega\gamma x} \leq p_x^V - \underline{p}_c^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT}, \forall x = [1] \quad (7-39)$$

$$P_{ct\omega\gamma x} \leq \bar{p}_c^C - p_{x-1}^V, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT}, \forall x \in [Nx] \quad (7-40)$$

$$P_{ct\omega\gamma x} \geq 0, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT}, \forall x \in \Omega^x \quad (7-41)$$

$$Wg_{wt\omega\gamma}^{Tank} + Wg_{wt\omega\gamma}^{WDU} = Wd_{wt\omega\gamma}^{WDU}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-42)$$

$$Wd_{wt\omega\gamma}^{WDU} = Wd_w^{peak} * Wd_{wt}^{profile}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-43)$$

$$Pd_{wt\omega\gamma}^{WDU} = \frac{Wg_{wt\omega\gamma}^{WDU}}{1000} * (PE_w^{WDU} + K_{joule}^{kwh} * PT_w^{WDU}), \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-44)$$

$$0 \leq Wg_{wt\omega\gamma}^{WDU} \leq Wg_w^{HC}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-45)$$

$$Wg_w^{HC} = \frac{Wg_w^{TDC}}{24}, \forall w \in \Omega^w, \forall t \in \Omega^T, \quad (7-46)$$

$$Wg_{wt\omega\gamma}^{Tank} = W_{wt\omega\gamma}^{Dis} - W_{wt\omega\gamma}^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-47)$$

$$0 \leq W_{wt\omega\gamma}^{Cha} \leq WPC_w^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-48)$$

$$0 \leq W_{wt\omega\gamma}^{Dis} \leq WPC_w^{Dis}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-49)$$

$$BT_{wt\omega\gamma}^{Cha} \text{ and } BT_{wt\omega\gamma}^{Dis} \text{ are binary}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-50)$$

$$BT_{wt\omega\gamma}^{Cha} + BT_{wt\omega\gamma}^{Dis} \leq 1, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-51)$$

$$W_{wt\omega\gamma}^{Cha} \leq M * BT_{wt\omega\gamma}^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-52)$$

$$W_{wt\omega\gamma}^{Dis} \leq M * BT_{wt\omega\gamma}^{Dis}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-53)$$

$$W_{wt\omega\gamma}^{Tank} = W_{w(t-1)\omega\gamma}^{Tank} + W_{wt\omega\gamma}^{Cha} * \Delta t - W_{wt\omega\gamma}^{Dis} * \Delta t, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-54)$$

$$0 \leq W_{wt\omega\gamma}^{Tank} \leq W_{C_w}^{Tank}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-55)$$

$$W_{wt\omega\gamma}^{Dis} * \Delta t \leq W_{w(t-1)\omega\gamma}^{Tank}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-56)$$

$$\sum_t W_{wt\omega\gamma}^{Dis} * \Delta t = \sum_t W_{wt\omega\gamma}^{Cha} * \Delta t, \forall w \in \Omega^w, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-57)$$

$$\begin{aligned} \sum_{c \in \Omega^C} p_{ct\omega\gamma}^C + \sum_{r \in \Omega^R} p_{rt\omega\gamma}^R + \sum_{s \in \Omega^S} p_{st\omega\gamma}^S - \sum_{d \in \Omega^D} p_{dt\omega\gamma}^D - p_{t\omega}^{DA} = p_{t\omega\gamma}^{sum}, \forall t \\ \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \end{aligned} \quad (7-58)$$

$$p_{t\omega\gamma}^{sum} \leq 10000 B_{t\omega\gamma}^{sum1}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-59)$$

$$p_{t\omega\gamma}^{sum} \geq -10000 B_{t\omega\gamma}^{sum2}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-60)$$

$$B_{t\omega\gamma}^{sum1} + B_{t\omega\gamma}^{sum2} \leq 1, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-61)$$

$$\begin{aligned} X_t^{lim} = \frac{\sum_{\omega\gamma} DA \text{ scenarios} - \sum_{\gamma} \text{highest RT scenarios}}{\text{average}(DA \text{ scenarios})} * 100, \forall t \\ \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \end{aligned} \quad (7-62)$$

$$2\beta - X_t^{lim} \leq 1000 B_{t\omega\gamma}^{sum1}, \forall t \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-63)$$

Most of the equations have been discussed earlier. In equation (7-2), the term $C_{ct\omega\gamma}^C$ was introduced to represent the operational cost (fixed and variable) of the conventional generator. Also, the terms U_{wt}^{WDU} and $p_{wt\omega\gamma}^{WDU}$ were added to account for the utility and the demand of the WDU respectively. In equations (7-5) and (7-6), the term $p_{wt\omega\gamma}^{WDU}$ was added to account for the demand of the WDU. The term $p_{ct\omega\gamma}^{C,max}$ is an intermediate variable for the maximum power generation of a conventional generator. Equations (7-18) to (7-20) represent the minimum and maximum limits of generation of the conventional generator. Equation (7-21) models both the ramp up and the startup ramp limits of the conventional generator. Similarly, equation (7-22) models the ramp down and shut down ramp limits of the conventional generator. Lastly, (7-23) represents the preparation of the conventional generator for shut down.

Each VPP will comprise the equations above for the DA market. However, each VPP will optimize its own objective independently and the common segments between the VPPs will be the EP and the electric grid/network. Next, the RT market equations will be presented in addition to the equations or methodology that govern the interaction of the VPPs and the EP together. The topology of the VPP cluster has been shown on Figure 6-2 and the flowchart describing the interaction between the VPP, and the EP was shown on Figure 6-1.

7.2 VPP Cluster RT Model

Based on the analysis and the studies presented earlier, the equations governing the RT market simulation have been selected as follows:

$$\max_{\Phi^{RT,S}} \sum_{\gamma \in \Pi^{RT}} \pi_{\gamma} \zeta_{\gamma} + \beta \left[\rho - \frac{1}{1-\alpha} \sum_{\gamma \in \Pi^{RT}} \pi_{\gamma} \mu_{\gamma} \right] \quad (7-64)$$

$$\begin{aligned} \zeta_{\gamma} = \sum_{t \in \Omega^T} \left[(\lambda_{t\gamma}^{DA} + r_{t\gamma}^{RT}) p_{t\gamma}^{RT} \Delta t + \sum_{d \in \Omega^D} U_{dt}^D p_{dt\gamma}^D \Delta t \right. \\ \left. - \sum_{w \in \Omega^{WDU}} U_{wt}^{WDU} p_{wt\gamma}^{WDU} \Delta t - \sum_{c \in \Omega^C} (C_c^C \Delta t + \bar{c}_{ct\gamma}^C \right. \\ \left. + \underline{c}_{ct\gamma}^C) \right], \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \end{aligned} \quad (7-65)$$

$$-\zeta_{\gamma} + \rho - \mu_{\gamma} \leq 0, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-66)$$

$$0 \leq \mu_{\gamma}, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT} \quad (7-67)$$

$$\begin{aligned} \sum_{c \in \Omega_n^C} p_{ct\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\gamma}^L \\ = p_{nt\gamma}^M + \sum_{d \in \Omega_n^D} p_{dt\gamma}^D + \sum_{w \in \Omega_n^{WDU}} p_{wt\gamma}^D, \forall n \in \Omega^M, \forall t \\ \geq \tau, \forall \gamma, \end{aligned} \quad (7-68)$$

$$\begin{aligned}
& \sum_{c \in \Omega_n^C} p_{ct\gamma}^C + \sum_{r \in \Omega_n^R} p_{rt\gamma}^R + \sum_{s \in \Omega_n^S} p_{st\gamma}^S - \sum_{\ell | s(\ell)=n} p_{\ell t\gamma}^L + \sum_{\ell | r(\ell)=n} p_{\ell t\gamma}^L \\
& = \sum_{d \in \Omega_n^D} p_{dt\gamma}^D + \sum_{w \in \Omega_n^{WDU}} p_{wt\gamma}^D, \forall n \in \Omega^N \setminus n \in \Omega^M, \forall t \\
& \geq \tau, \forall \gamma,
\end{aligned} \tag{7-69}$$

$$\tilde{p}_t^{\text{DA}} + p_{t\gamma}^{\text{RT}} = \sum_{n \in \Omega^M} p_{nt\gamma}^M, \forall t \geq \tau, \forall \gamma, \tag{7-70}$$

$$p_{\ell t\gamma}^L = B_\ell(\delta_{s(\ell)t\gamma} - \delta_{r(\ell)t\gamma}), \forall \ell \in \Omega^L, \forall t \geq \tau, \forall \gamma, \tag{7-71}$$

$$-\bar{P}_\ell^L \leq p_{\ell t\gamma}^L \leq \bar{P}_\ell^L \quad \forall \ell \in \Omega^L, \forall t \geq \tau, \forall \gamma \tag{7-72}$$

$$\delta_{nt\gamma} = 0, n: \text{ref.}, \forall t \geq \tau, \forall \gamma, \tag{7-73}$$

$$-\pi \leq \delta_{nt\gamma} \leq \pi, \forall n \in \Omega^N \setminus n: \text{ref.}, \forall t \geq \tau, \forall \gamma, \tag{7-74}$$

$$\underline{P}^V \leq \tilde{p}_t^{\text{DA}} + p_{t\gamma}^{\text{RT}} \leq \bar{P}^V, \forall t \geq \tau \tag{7-75}$$

$$-\bar{P}_n^M \leq p_{nt\gamma}^M \leq \bar{P}_n^M, \forall n \in \Omega^M, \forall t \geq \tau, \forall \gamma, \tag{7-76}$$

$$\sum_{t=1}^{\tau-1} \tilde{p}_{dt}^D \Delta t + \sum_{t=\tau}^{|\Omega^T|} p_{dt\gamma}^D \Delta t \geq \underline{E}_d^D, \forall d \in \Omega^D, \forall \gamma, \quad (7-77)$$

$$\underline{p}_{dt}^D \leq p_{dt\gamma}^D \leq \bar{p}_{dt}^D, \forall d \in \Omega^D, \forall t \geq \tau, \forall \gamma, \quad (7-78)$$

$$-R_d^{D,D} \Delta t \leq p_{dt\gamma}^D - p_{d(t-1)\gamma}^D \leq R_d^{D,U} \Delta t, \forall d \in \Omega^D, \forall t \geq \tau, \forall \gamma, \quad (7-79)$$

$$\underline{p}_c^C u_{ct\gamma}^C \leq p_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \Pi^{\text{RT}} \quad (7-80)$$

$$p_{ct\gamma}^C \leq p_{ct\gamma}^{C,\max}, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \Pi^{\text{RT}} \quad (7-81)$$

$$p_{ct\gamma}^{C,\max} \leq \bar{p}_c^C u_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \Pi^{\text{RT}} \quad (7-82)$$

$$\begin{aligned} p_{ct\gamma}^{C,\max} - p_{c(t-1)\gamma}^C \\ \leq R_c^{C,U} * \Delta t * u_{c(t-1)\gamma}^C + R_c^{C,SU} * \Delta t \\ * (u_{ct\gamma}^C - u_{c(t-1)\gamma}^C) + \bar{p}_c^C (1 - u_{ct\gamma}^C), \forall c \in \Omega^C, \forall t \\ \in \Omega^T, \forall \gamma \Pi^{\text{RT}} \end{aligned} \quad (7-83)$$

$$\begin{aligned} p_{c(t-1)\gamma}^C - p_{ct\gamma}^C \\ \leq R_c^{C,D} * \Delta t * u_{ct\gamma}^C + R_c^{C,SD} * \Delta t * (u_{c(t-1)\gamma}^C - u_{ct\gamma}^C) \\ + \bar{p}_c^C (1 - u_{c(t-1)\gamma}^C), \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \Pi^{\text{RT}} \end{aligned} \quad (7-84)$$

$$\begin{aligned}
p_{ct\omega\gamma}^{C,\max} &\leq \bar{P}_c^C * u_{c(t+1)\omega\gamma}^C + R_c^{C,SD} * \Delta t * (u_{ct\omega\gamma}^C - u_{c(t+1)\omega\gamma}^C), \forall c \\
&\in \Omega^C, \forall (t \leq TT - 1) \in \Omega^T, \forall \omega \in \Pi^{DA}, \forall \gamma \in \Pi^{RT}
\end{aligned} \tag{7-85}$$

$$\bar{C}_c^C(u_{ct\gamma}^C - u_{c(t-1)\gamma}^C) \leq \bar{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \tag{7-86}$$

$$0 \leq \bar{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \tag{7-87}$$

$$\underline{C}_c^C(u_{c(t-1)\gamma}^C - u_{ct\gamma}^C) \leq \underline{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \tag{7-88}$$

$$0 \leq \underline{c}_{ct\gamma}^C, \forall c \in \Omega^C, \forall t \geq \tau, \forall \gamma, \tag{7-89}$$

$$e_{st\gamma}^S = e_{s(t-1)\gamma}^S + \eta_s^{S,C} p_{st\gamma}^{S,C} \Delta t - \frac{p_{st\gamma}^{S,D}}{\eta_s^{S,D}} \Delta t, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \tag{7-90}$$

$$\underline{E}_{st}^S \leq e_{st\gamma}^S \leq \bar{E}_{st}^S, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \tag{7-91}$$

$$0 \leq p_{st\gamma}^{S,C} \leq \bar{P}_s^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \tag{7-92}$$

$$0 \leq p_{st\gamma}^{S,D} \leq \bar{P}_s^{S,D}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma, \tag{7-93}$$

$$p_{st\gamma}^S = p_{st\gamma}^{S,D} - p_{st\gamma}^{S,C}, \forall s \in \Omega^S, \forall t \geq \tau, \forall \gamma \tag{7-94}$$

$$0 \leq p_{rt\gamma}^R \leq \tilde{p}_{rt\gamma}^{R,A}, \forall r \in \Omega^R, \forall t = \tau, \forall \gamma \quad (7-95)$$

$$0 \leq p_{rt\gamma}^R \leq p_{rt\gamma}^{R,A}, \forall r \in \Omega^R, \forall t > \tau, \forall \gamma \quad (7-96)$$

$$p_{t\gamma}^{RT} \leq p_{t\gamma'}^{RT}, \quad \text{if } \lambda_{t\gamma}^{RT} \leq \lambda_{t\gamma'}^{RT}, \forall t \in \Omega^T, \forall \gamma, \forall \gamma' \quad (7-97)$$

$$p_{t\gamma}^{RT} = p_{t\gamma'}^{RT}, \quad \text{if } \lambda_{t\gamma}^{RT} = \lambda_{t\gamma'}^{RT}, \forall t \in \Omega^T, \forall \gamma, \forall \gamma' \quad (7-98)$$

$$c_{ct\gamma}^C = c_c^{C,F} * u_{ct\gamma}^C + \sum_{x=1}^{Nx} c_x^V * P_{ct\gamma x}, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT}, \quad (7-99)$$

$$p_{ct\gamma}^C = \underline{p}_c^C * u_{ct\gamma}^C + \sum_{x=1}^{Nx} P_{ct\gamma x}, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT}, \quad (7-100)$$

$$P_{ct\gamma x} \leq p_x^V - p_{x-1}^V, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT}, \forall x \in [2, Nx - 1] \quad (7-101)$$

$$P_{ct\gamma x} \leq p_x^V - \underline{p}_c^C, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT}, \forall x = [1] \quad (7-102)$$

$$P_{ct\gamma x} \leq \bar{p}_c^C - p_{x-1}^V, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT}, \forall x = [Nx] \quad (7-103)$$

$$P_{ct\gamma x} \geq 0, \forall c \in \Omega^C, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT}, \forall x \in \Omega^x \quad (7-104)$$

$$Wg_{wt\gamma}^{Tank} + Wg_{wt\gamma}^{WDU} = Wd_{wt\gamma}^{WDU}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-105)$$

$$Wd_{wt\gamma}^{WDU} = Wd_w^{peak} * Wd_{wt}^{profile}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-106)$$

$$Pd_{wt\gamma}^{WDU} = \frac{Wg_{wt\gamma}^{WDU}}{1000} * (PE_w^{WDU} + K_{joule}^{kwh} * PT_w^{WDU}), \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-107)$$

$$0 \leq Wg_{wt\gamma}^{WDU} \leq Wg_w^{HC}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-108)$$

$$Wg_w^{HC} = \frac{Wg_w^{TDC}}{24}, \forall w \in \Omega^w, \forall t \in \Omega^T, \quad (7-109)$$

$$Wg_{wt\gamma}^{Tank} = W_{wt\gamma}^{Dis} - W_{wt\gamma}^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-110)$$

$$0 \leq W_{wt\gamma}^{Cha} \leq WPC_w^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-111)$$

$$0 \leq W_{wt\gamma}^{Dis} \leq WPC_w^{Dis}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-112)$$

$$BT_{wt\gamma}^{Cha} \text{ and } BT_{wt\gamma}^{Dis} \text{ are binary}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-113)$$

$$BT_{wt\gamma}^{Cha} + BT_{wt\gamma}^{Dis} \leq 1, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-114)$$

$$W_{wt\gamma}^{Cha} \leq M * BT_{wt\gamma}^{Cha}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-115)$$

$$W_{wt\gamma}^{Dis} \leq M * BT_{wt\gamma}^{Dis}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-116)$$

$$W_{wt\gamma}^{Tank} = W_{w(t-1)\gamma}^{Tank} + W_{wt\gamma}^{Cha} * \Delta t - W_{wt\gamma}^{Dis} * \Delta t, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-117)$$

$$0 \leq W_{wt\gamma}^{Tank} \leq WC_w^{Tank}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-118)$$

$$W_{wt\gamma}^{Dis} * \Delta t \leq W_{w(t-1)\gamma}^{Tank}, \forall w \in \Omega^w, \forall t \in \Omega^T, \forall \gamma \in \Pi^{RT} \quad (7-119)$$

$$\sum_t W_{wt\gamma}^{Dis} * \Delta t = \sum_t W_{wt\gamma}^{Cha} * \Delta t, \forall w \in \Omega^w, \forall \gamma \in \Pi^{RT} \quad (7-120)$$

The equations, variables, and parameters have all been discussed earlier. This set of equations for the RT market are applicable to each VPP but every VPP has its own independent system.

7.3 VPP Cluster EP Model

The EP is connected to the VPPs as presented on Figure 6-2. However, it is not a straightforward process to manage the EP in the optimization problem as it may seem from Figure 6-2. First, as shown in the flowchart of Figure 6-1, the VPP will run normally

without including the EP in its optimization scope. This is because the EP is an independent entity and it is not directly affecting the VPP financially nor technically. Once the VPP, any VPP, fails to meet its demand, or fails to participate into the electricity markets and reaches a point of imbalance between generation and supply, the EP will be included into the optimization problem as a source.

Now, this source can be considered as a big storage source with the details provided on Table 7-1. Once the EP provides the VPP with some energy, the VPP has to pay this energy back in addition to any losses made during the process in order to ensure that the EP will return back to a 100% state of charge. To return this energy back, during the next hour or hours, the EP will have to be included into the optimization problem as a load in order to start receiving power instead of giving it. This load will have the technical parameters provided in Table 7-2.

Table 7-1 EP data as a source

Definition	Value
Bus Number	6
Line Number	7
Line From Bus #	1
Line To Bus #	6
Line Capacity (MW)	1000
Line Susceptance (S)	300
Unit Type	Storage

Definition	Value
Maximum Capacity (MWh)	1000
Minimum Capacity (MWh)	0
Charge Rate (MW/h)	500
Discharge Rate (MW/h)	500
Initial Energy (MWh)	1000

Table 7-2 EP data as a load

Definition	Value
Bus Number	6
Line Number	7
Line From Bus #	1
Line To Bus #	6
Line Capacity (MW)	1000
Line Susceptance (S)	300
Unit Type	Load
Maximum Demand (MW)	Variable (1000)
Minimum Demand (MW)	0
Ramp Up Rate (MW/h)	1000
Ramp Down Rate (MW/h)	1000
Initial Demand (MWh)	0
Daily Minimum Energy Demand (MWh)	0
Utility (\$)	100

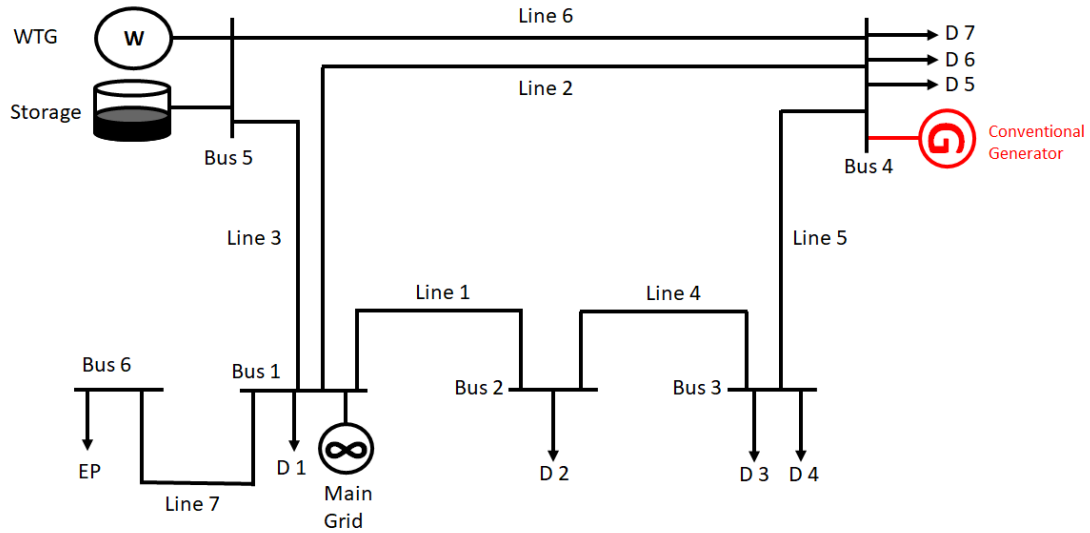


Figure 7-1 5-Bus network with EP load

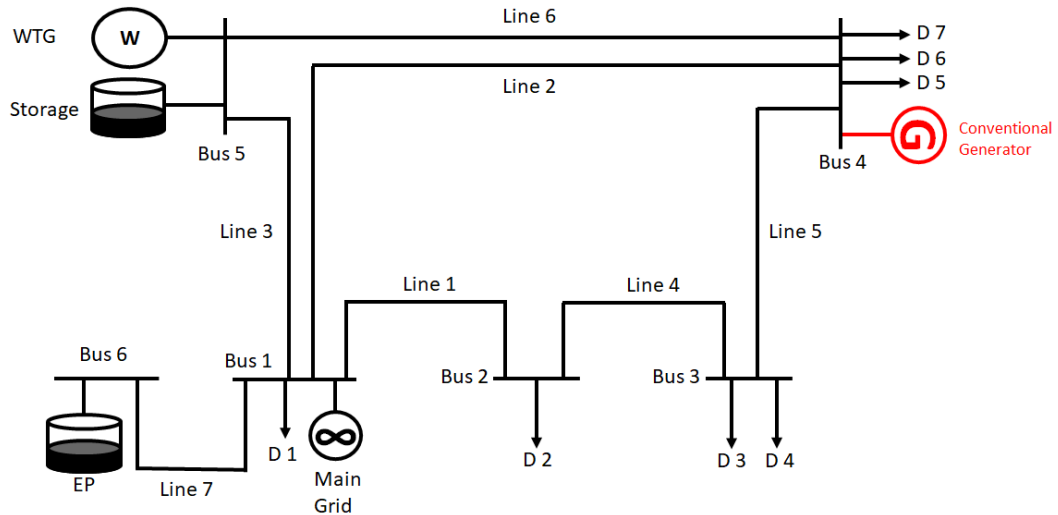


Figure 7-2 5-Bus network with EP source

As it can be seen on the tables and figures above, the EP will act as a source or as a load based on the status of the VPP. If the VPP does its scheduling optimization and finds out it cannot meet the demand, it will add the EP in the dispatch optimization as a source. Right after using the EP as a source, the VPP will be forced to connect the EP as a load at all the coming hours until it returns back all the energy it has taken from the EP. After that, the

VPP can disconnect the EP from the optimization problem until needed again in a similar manner.

As a source, the EP is limited only by its charge and discharge rates which are set to 500 MW/h. When the EP acts as a load however, some points must be considered. The first thing is that the EP should not be a mandatory load that could lead the VPP to a failure while its core purpose is to help avoiding the failures. Thus, the EP as a load will have a minimum daily energy demand of zero and a minimum hourly demand of zero. This will allow the VPP to give it no power transfer at all if connecting it as a load could lead to any failure. But this does not guarantee that the VPP will ever pay that energy back to the EP. Thus, to encourage the VPP, in terms of optimization programming, to pay that energy back to the EP, the utility of the EP will be set to a high value, 100. This scheme will make the optimization problem always give priority to paying the energy back to the EP while also having the ability not to give it any energy if that could lead the VPP to any power imbalance.

7.4 VPPs Input Data

To make a VPP cluster, there has to be more than one VPP. Therefore, three VPPs will be used. The three VPPs will have the same structure as shown on Figure 5-1. However, for simulation purposes, the three VPPs cannot be 100% identical. Therefore, the data of each VPP will be changed in order to have a different VPP with the same structure of the original one. Thus, the first main difference is that each VPP will have to make its own forecast for

the DA market price, RT market price, and wind power output. The three VPPs will be considered in the same region and of course they are all simulated on the same day. Hence, the forecasted data should be similar but not the same.

The second difference is that the first VPP will be made very conservative with a weighing factor equals to three. The weighing factor affects both the CVaR and the reliability constraints as discussed earlier. This is expected to reduce the total profit but result in a more secure operation. For the second VPP, the maximum demand of all loads will be equal to 40% of the original value used in the first VPP. Accordingly, the minimum daily energy demand of those loads shall be multiplied by 40%. In addition to the drop in demand, the wind power generator will be multiplied by 20. In other words, 20 wind power plants will be used instead of only one. Now, due to this extra generation and less demand, the VPP operator will set the weighing factor to zero. With more generation and less demand, the VPP operator gets more confidence risking for higher profit as the risk is obviously reduced with the extra generation and less demand.

Lastly, the third VPP will not be modified. This means that the weighing factor will be kept equal to one, and the generation and demand are neither be increased nor decreased. The first bus of each VPP will be connected to both the EP and the main grid. The line that will connect each VPP to the EP will be rated with 1000 MW capacity and a susceptance of 300 S. The rest of the parameters remain unchanged.

7.5 VPP Cluster Simulation

The three VPPs have been interconnected with the EP and simulated. A single VPP with an EP has been simulated before. In this section, two VPPs with some changes from the original VPP are added to the previously presented system of one VPP and one EP. The three VPPs are independent but they share the same EP. They are also all connected to the main grid. When analyzing the power exchange, demand and generation of each VPP, they can be looked at independently. Figure 7-3 for example shows the generation, demand, power traded, and power exchange with the EP for the first VPP. First, the conventional generator covers the biggest portion of generation after which the storage and wind power sources cover a smaller portion. The figure is a stacked figure where the output of every source is stacked on or added to the output of the previous source. The power traded in both the Day-ahead and real-time markets is stacked also on the top of the three generation sources in order to meet the demand marked with the green line on the top.

It can be seen that the demand perfectly matches the generation at all hours. Thus, the system has not failed at any of the 24 hours. This is because as highlighted earlier, the first VPP was considered a very conservative system where the weight of the CVaR was set to three. It is worth noting that the weight is also part of the reliability equations. And a weight of three is not a small weight to be considered for the reliability equations. Thus, the first VPP has considered a high reliability weight which has resulted into a system that did not fail a single hour during the day though the original system without EP and without reliability constraints has failed four hours in one day. This conservativeness will definitely have effect onto the net profit.

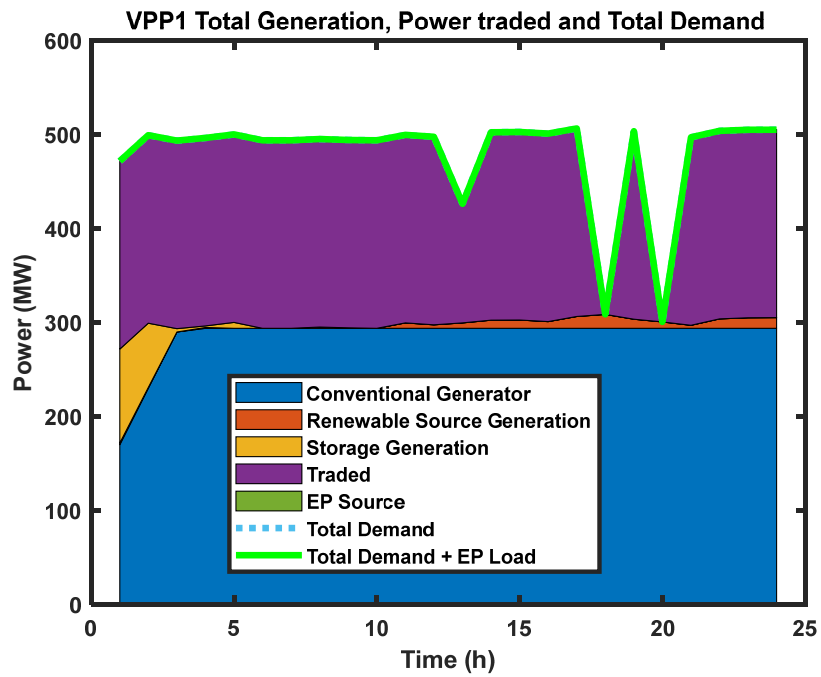


Figure 7-3 VPP cluster, VPP1 demand and generation

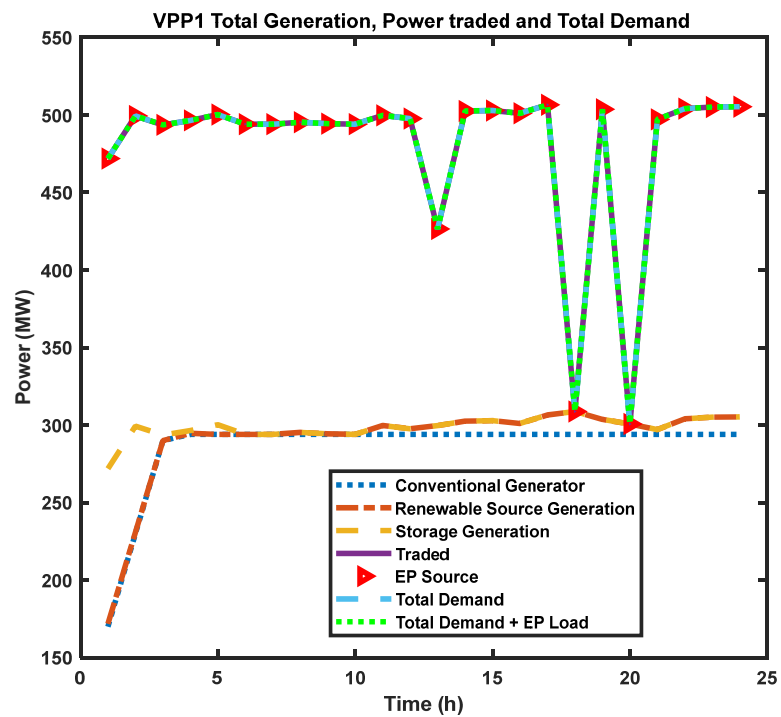


Figure 7-4 VPP cluster, VPP1 demand and generation – second figure

Figure 7-4 is the exact same figure as the one before it. The only difference is that the first one is a stacked area figure while this is a stacked line figure. It is only presented for clearer representation of Figure 7-3. It is important to note that since there has been no failure at all, the first VPP has not interacted with the EP at all. Therefore, there is no power exchange with the EP shown on the figures above.

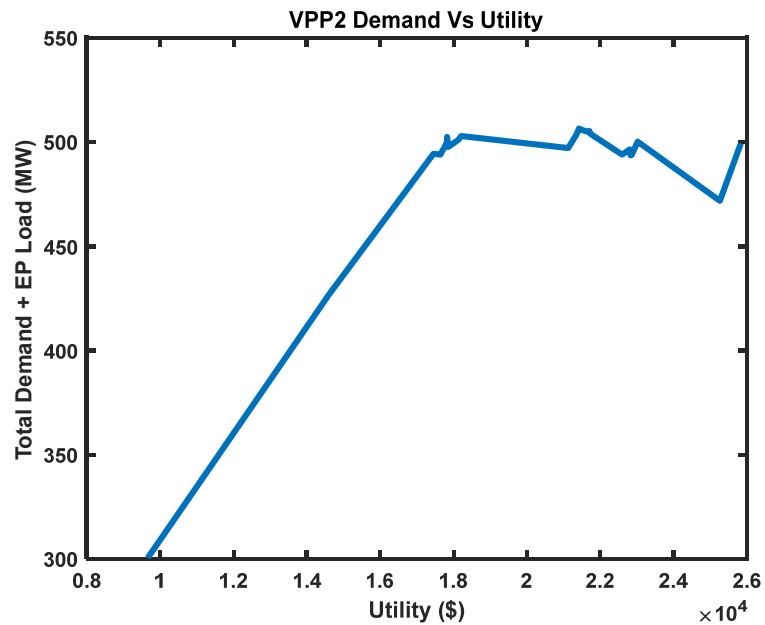


Figure 7-5 VPP cluster, VPP1 demand vs utility

On Figure 7-5, the demand versus utility is shown. As expected, the more the utility price increases, the more the VPP tries to make more profit by increasing the demand. Since the demand is flexible with a minimum and a maximum limit, the VPP will tend to be closer to the lower limit when the utility price is low and closer to the maximum limit when the utility price is high. It is however not the only deciding factor. It is possible that with the change of utility that the VPP would not change the demand as the Day-ahead and real-time market prices play an important role in the decision making in addition to all the other

variables of the optimization problem. The same figures can be assessed for the second and the third VPPs.

Figure 7-6 shows that the second VPP has a completely different interaction of components compared to the first VPP. First, the conventional generator is not running at its maximum limits as it was the case for the first VPP. This is because the second VPP has the maximum demand dropped to 40% of the original value of the first VPP and also the minimum daily energy demand dropped to 40% accordingly. Also, the wind power plant has got 20 units now instead of one compared to the original case of the first VPP. Due to this higher generation capability and lower demand, this VPP operator decided to consider zero weighing factor which makes the system risk neutral.

The wind power generation is much higher due to the increase of the wind power units. Additionally, the storage system is now charging and discharging at different hours of the day unlike the case of the first VPP where the storage system got completely depleted at the first few hours of the day after which it did not charge again. Some areas of the storage system are hidden due to the overlap with the traded power portion. This is why Figure 7-7 is presented in order to show those hidden areas. When the traded power is below the green line of demand, it means it is added to the total generation i.e. the VPP has purchased power from the network. In contrary, if the traded power is above the green line of demand, it means it is subtracted from the total generation i.e. the VPP has sold power to the network.

The system has failed at the 20th hour of the day as it did not consider any risk or reliability constraints at all by setting the weight to zero. This is where the EP was considered as a source of power in order to make up for the imbalance between generation and demand. The EP source has covered the green area on the figure which has led the system back to balance and setting the demand to be equal to the generation at the 20th hour. Right after the 20th hour, the VPP has to start returning back the energy it has taken from the EP. Thus, the EP will act as a load from the 21st hour onwards until the VPP returns all the energy taken from the EP back to the EP.

During the 21st and 22nd hours, the VPP paid back the energy taken on the 20th hour. The green line shows the total demand of the VPP added to the demand of the EP when acting as a load. It can be seen that the demand has matched the generation until the end of the day. The cyan line which shows the total demand of the VPP only without the EP when acting as a load shows that the demand on the 21st and 22nd hours of the day was lowered in order to return back the energy taken from the EP. Thus, the difference between the cyan and green lines is the energy transferred from the second VPP to the EP.

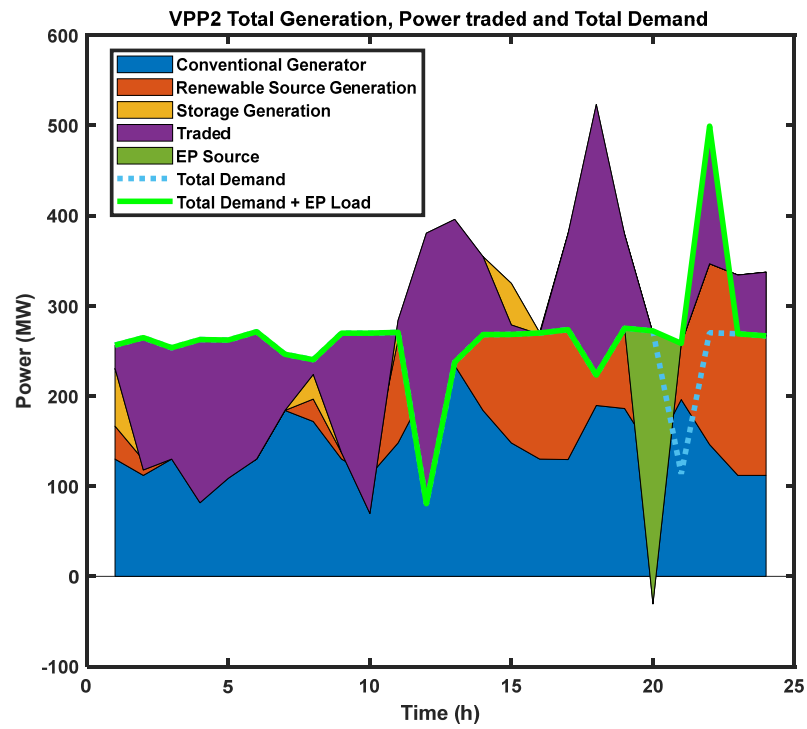


Figure 7-6 VPP cluster, VPP2 demand and generation

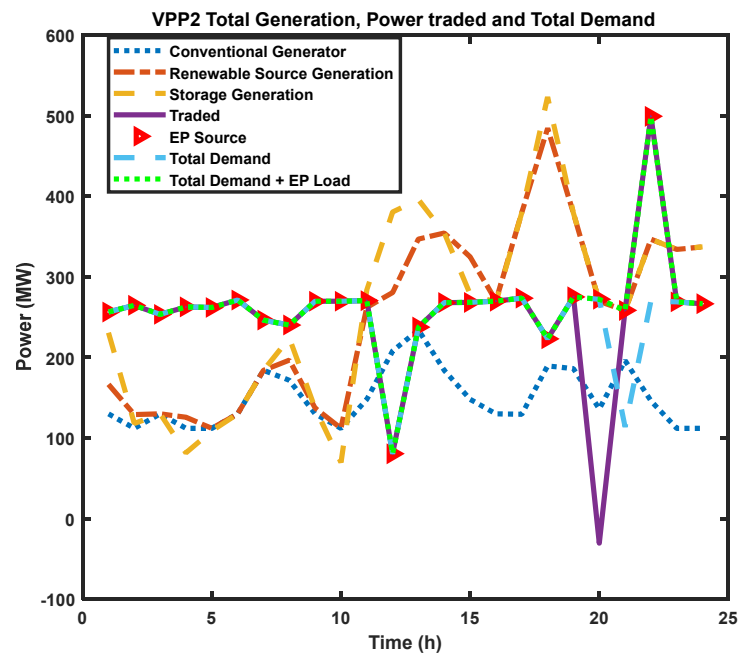


Figure 7-7 VPP cluster, VPP2 demand and generation – second figure

Figure 7-8 shows the demand against the utility. As expected from the explanation of the same figure for the first VPP, the higher the utility, the more the demand is expected to be. This is because this is a centralized and partially comprehensive control scheme where the VPP tries to maximize its own profit from every source. If this is replaced with a fully distributed control scheme, the scenario might be totally opposite to this one. Since each demand will pay utility, the demand is expected to decrease with the increased utility since the increased utility means higher payment the demand has to make.

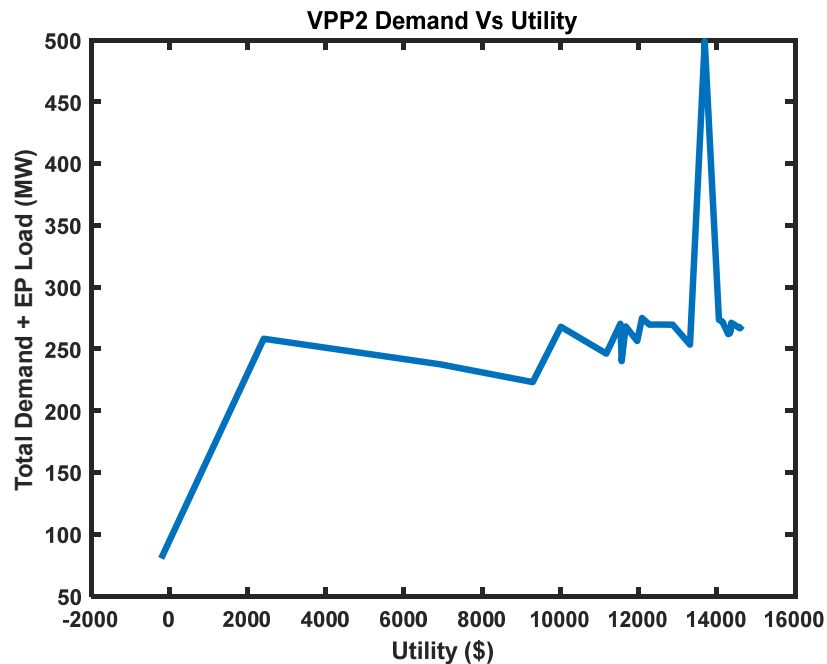


Figure 7-8 VPP cluster, VPP2 demand vs utility

The third VPP is the last VPP in the cluster. It has a different behavior from the first two VPPs but it is very similar to the first VPP. This is because the third VPP has decided to go with a weighing factor of one instead of three which was the case for the first VPP. Of course, the three VPPs are different in terms of the forecast of the three uncertain

parameters. The uncertain parameters are not expected to cause a big difference in the results though as the three VPPs are considered in the same region where their forecast will not be the same but should be relatively close. The same behavior of the first VPP is seen here except for the failure that happened at the 18th hour for the third VPP. Therefore, considering a lower weighing factor has resulted into this failure mainly.

The green area is the power imbalance difference at the 18th hour that was covered by the EP which acted as a source during that hour. During the hours after the 18th hour, the EP will act as a load until the third VPP pays back all the energy taken from the EP. The dashed cyan line shows the demand of the VPP without the consideration of the load of the EP. The green line shows the total demand of the VPP in addition to the demand of the EP. It can be seen that for three hours after the 18th hour, there was a difference between the green and cyan lines. This means that the VPP took some energy on the 18th hour from the EP and paid it back during the 19th, 20th, and 21st hours. The difference between the cyan and green lines represents the power delivered from the VPP to the EP.

Figure 7-10 again shows the same thing as shown on Figure 7-9 except that it is shown as lines instead of areas. The total power generation and exchange with the network and EP is presented as red triangles on the figure. The total demand of the VPP in addition to the demand of the EP are shown as a dashed green line on the same figure. Both the dashed green line and the red triangles are at perfect match during the 24 hours. Thus, the EP has successfully helped both the second and the third VPPs to maintain their balance at all hours of failure.

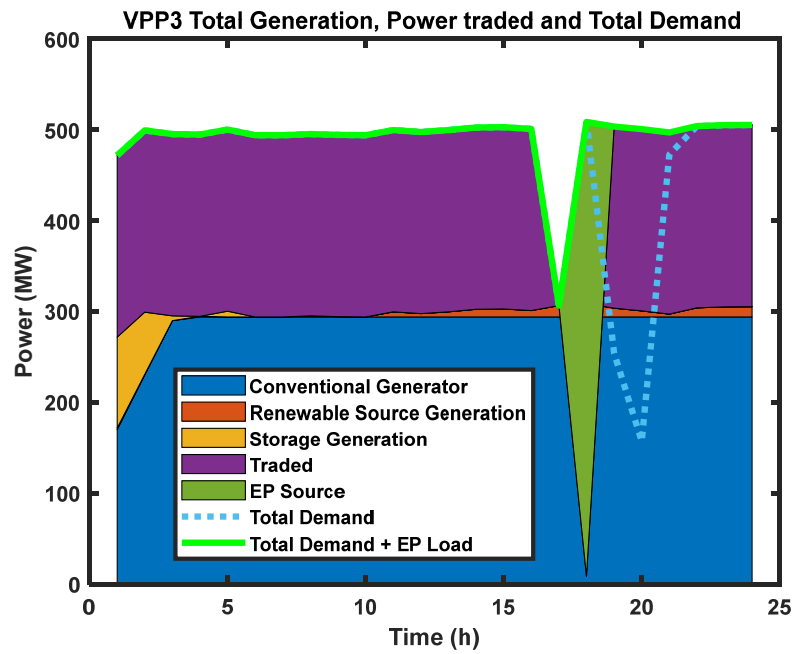


Figure 7-9 VPP cluster, VPP3 demand and generation

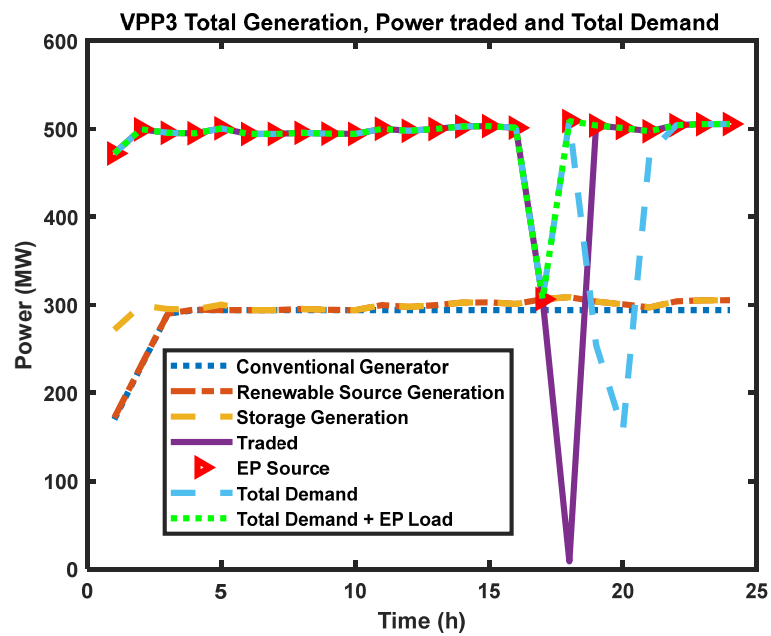


Figure 7-10 VPP cluster, VPP3 demand and generation – second figure

The last figure for the third VPP is the utility versus the demand. Figure 7-11 shows a different behavior for the third VPP compared to the previous two. It can be seen that the demand was steady regardless to the utility value. This proves the aforementioned theory that the utility value is not the only deciding factor for the behavior of the demand. The Day-ahead and real-time market prices are also critical factors. The only issue is the dip in the middle of the figure which happened at the 17th hour of the day. Though this issue is not actually an issue since the VPP has maintained balance between the generation and demand. It is however a behavior that requires an explanation. This happened because the 17th hour is the only hour of the day where the power traded with the DA market and the RT market was zero. This can be seen on Figure 7-9 where it is noticed that there is no purple area at the 17th hour.

Due to this zero power trade, the demand was lowered in order to maintain balance. The trade has not happened during that hour due to the risk averse constraints, the DA market prices, the RT market prices, and their relativeness to the utility value. The VPP found it more risk averse and more profitable not to trade during this hour. And for that, the VPP has decided to lower the demand during this hour. It is interesting when considering that this is one major reason why the demand was high when the utility value was low. It is clear why the demand is high when the utility value is high. But the question is why was the demand high when the utility was low? This is because the dip in demand at the 17th hour had to be covered during other hours without breaking the energy balance constraints. And since no more demand could have been added to the hours where the utility is high, the demand was added to the hours where the utility is low.

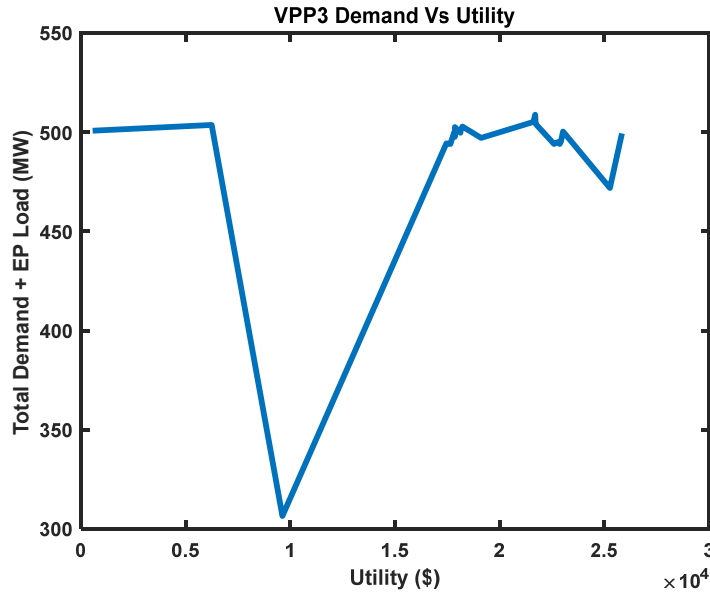


Figure 7-11 VPP cluster, VPP3 demand vs utility

Those different VPPs with different specifications and outcomes highlight some crucial points such as the effectiveness and importance of the reliability constraints which have saved the first VPP from any failure. They also show the effectiveness of the proposed VPP cluster by helping the second and third VPPs to avoid the failures that happened to them at different hours of the day. This is clearly seen through Figure 7-12 where the power exchange between the EP and all the VPPs is shown. The first VPP did not take or give any power while the second and third VPPs have exchanged power with the EP. The second VPP is shown as a purple area while the third VPP is shown as a green area. The dip at the 18th hour for the third VPP is the point at which the third VPP failed and got supported by the EP. This point is negative as it represents power drawn from the EP. After that, the green curve is on the positive side as the VPP starts paying that energy back to the EP. The same case applies to the second VPP but starting from the 20th hour.

The summation of the power exchange of each VPP with the EP is shown as the orange area. The EP starts with 1000 MWh at the zeroth hour and it stays like that until the 18th hour as shown by the black line. Then, the SOC of the EP drops down from the 18th hour to the 22nd hour. By the 22nd hour, all the energy is returned back to the EP and the EP returns to a 1000 MWh SOC.

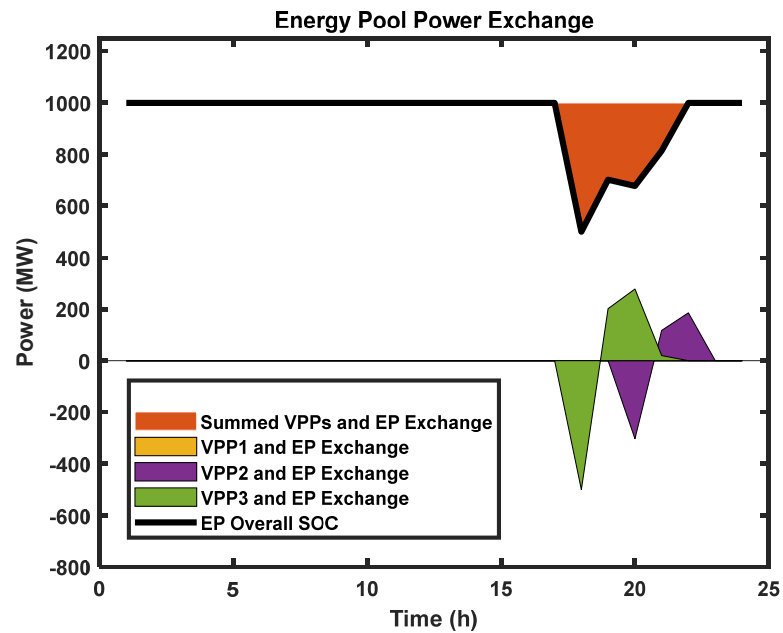


Figure 7-12 EP power exchange - all VPPs

A special focus is put onto the interaction of the storage system of each VPP with the system. This is because as seen on Figure 7-13, for the first and third VPPs, the storage is depleted at the early hours after which it did not charge. On the other hand, the second VPP goes through cycles of discharge and charge. To explain the behavior of the second VPP storage, the changes made to build the second VPP must be looked at. The generation of the wind power has increased 20 times by the increase of the number of units. Also, the demand was dropped to 40% of its value. This abundance in power compared to the other

two VPPs has resulted into this behavior. For the first and third VPPs, the VPPs were trying to maximize their profit through power exchange in the Day-ahead and real-time markets in addition to the profit from the utility. Since the load was big for those two cases and the utility was high, the VPPs tried to feed as much load as possible. After that, the VPPs tried to make the maximum possible profit from the price difference between the Day-ahead and real-time markets.

For the second VPP, the demand was reduced dramatically which means that after feeding the highest amount of demand that makes high profit, the VPP will turn to make the maximum profit possible by utilizing the price difference between the Day-ahead and real-time markets. This could mean that the VPP may have to buy power more than its need to meet the demand. This is where the role of the storage comes to help maximizing the profit. The storage is utilized to store that excess energy to be sold later for profit maximization. This could imply that the storage system for the first and second VPPs were not really needed for power balance purposes. They did not also participate well in profit maximization as in the case of the second VPP. Therefore, the first and third VPPs may need to do more accurate system sizing/ balance. This is however not the main purpose of the VPPs as the VPPs try to increase the number of participants into the VPPs based on which the VPPs try to maximize the profit.

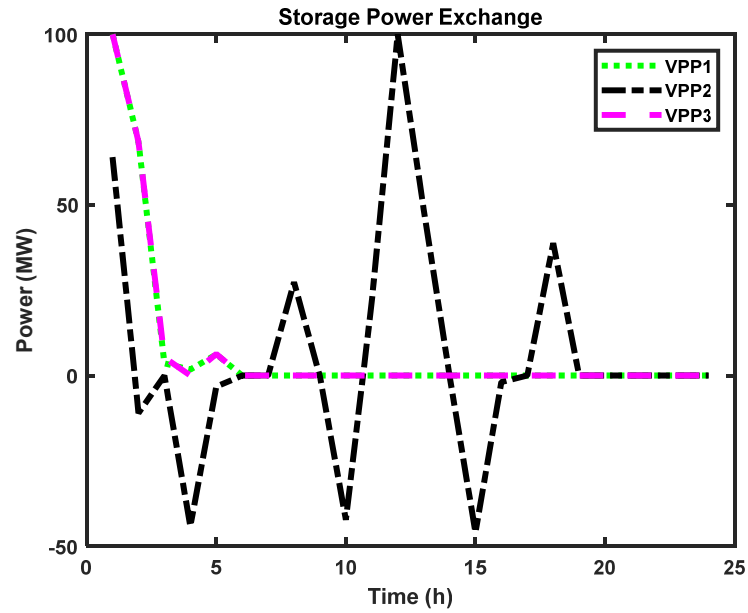


Figure 7-13 Storage power exchange - all VPPs

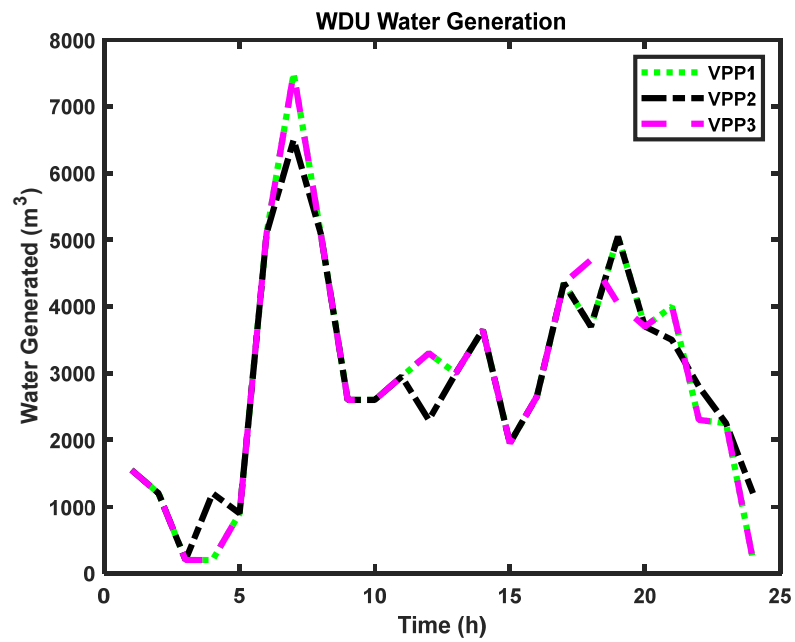


Figure 7-14 WDU water generation - all VPPs

Lastly, Figure 7-14 focuses on the specific demand considered which is the WDU.

Considering the differences between the VPPs, especially the difference in the storage and

conventional generator behaviors, it is expected that the WDU could behave differently as well. Nevertheless, the curve of the WDU water generation for the three VPPs is very similar. The reasons behind this are: first, the WDU is considered an independent load, though being part of the VPP, that optimizes its own cost which makes it less affected by the changes made to the VPP. Second, the WDU parameters were not changed for any of the three cases of the three VPPs.

The third reason for this behavior is that the load profile of the WDU is pre-defined for each hour. The fact that the water load profile is fixed makes this load semi-flexible to inflexible. The only flexibility of the WDU is its use of the tank which helps in adding a flexibility factor to the demand. Thus, it is probably more profitable if the water load profile of the WDU was made with minimum and maximum range as the flexible electrical loads. This would help utilizing the water tank more, give higher flexibility to the WDU, and allow for bigger opportunity for profit maximization.

CHAPTER 8

CONCLUSION AND FUTURE WORK

8.1 Conclusion

In conclusion, based on the literature review, analysis, modelling, development of models, simulations, and results shown above, the objectives have been achieved. First, a literature survey on the linear programming models existing in literature was made and multiple models have been presented and discussed. Based on these models, the stochastic model with risk consideration was selected for its comprehensiveness, balance between risk consideration, conservativeness and accuracy. The deterministic models and the models without risk consideration were simpler and use less computational time. However, these models were risk neutral and they could cause a big deviation from the expectation and big reduction in profit. Therefore, a stochastic model with risk consideration, though taking more time, and having a bit of increased complexity, was a better choice. This is because it considers risk, considers multiple scenarios, and does not suffer from severe conservativeness which is a drawback of using the robust optimization models. Also, the data availability is easier for the stochastic models over the robust models though both are available.

The proposed VPP model includes multiple and different types of units where a conventional generator is included, renewable energy source, flexible loads, energy storage system, and of course the rest of the components of a typical microgrid. The VPP participates in both the Day-ahead and real-time markets. The main objectives of the VPP are to minimize the operational cost, and increase the profit made through feeding the loads or interacting with the electricity markets. Additionally, a water desalination unit is added as a specific type of load. It is a load that actually has its own load which is the water demand. The WDU has a tank which is a storage medium that helps in managing the fluctuations in water demand and also helps in reduction the cost of the electric demand of the WDU.

Next, after developing this VPP model, another critical objective was added which is the reliability of the VPP. The reliability here refers to trying to ensure no failure in power balance at all the trading hours of the day. Therefore, reliability constraints have been developed which through simulations have proven being very effective in reducing and even eliminating the failures. This of course comes with the cost of reduction in profit. This is expected as reliability comes with a price. It is still better and cheaper to give up on a small portion of the profit for the security of the system as the cost of failure is much higher. By this the VPP has achieved three main objectives: maximizing the profit, reducing the operational cost, and increasing the reliability of the system.

Another proposed model was SOS2 which is a method for representing piecewise linear functions in linear programming. This was claimed to be faster than representing the

piecewise linear functions as a set of constraints. In literature, the variable generator cost is represented as a set of constraints that model the piecewise linear function of the variable generation cost. Thus, the SOS2 representation was proposed and tested in this research. It was found that the SOS2 representation took 50% extra time compared to the conventional constraints representation. This however contradicts the claim in [182] which says that the SOS2 constraints have one major benefit over the regular constraints which is the faster simulation. This could be due to the size of the system. It could be that this claim is valid for specific types of simulations, linear programming solving techniques, small or big number of variables, or some other factors that the authors did not clarify. In conclusion to this point, representing a piecewise linear function through a set of constraints is faster in simulation than SOS2 representation.

Another issue that was considered is that the reliability could be improved by the increase of the number of scenarios used. The more scenarios used, the higher the chances that there could be some scenarios that would cover some worse areas in terms of prices or power generation. Thus, the number of scenarios was increased and compared to the reliability constraints. It was found that the reliability constraints were much better at mitigating failures and they have also taken about 15% of the time taken when the number of scenarios was increased. Also, increasing the number of scenarios is computationally very demanding especially in terms of memory need. Therefore, the reliability constraints are extremely effective without causing any big need for computational time or memory.

The idea of a VPP cluster was introduced which was never discussed in literature before. In literature, a microgrid cluster is discussed where multiple microgrids are interconnected through an energy pool. The energy pool is a common source of power to back up any microgrid when needed. Those microgrids can be AC or DC. For DC microgrids, the main objective of the EP is to watch for the voltage level of the DC bus. Based on this, the EP can detect any power mismatch between demand and generation and back up that microgrid when needed. For AC microgrids, the EP watches the frequency. The frequency deviation is the triggering signal for the EP to back up the microgrid. Nonetheless, this concept was not discussed for VPPs since VPPs are already connected to the network and any power mismatch is expected to be balanced through the market. This is however not necessarily true as presented in this research. The VPP might fail to participate into the electricity market at all at some hours of the day. In this case, there is no need to look at any DC bus voltage or frequency deviation since the power imbalance is already clear through the results of the electricity trading schedule and the optimized solution of the VPP scheduling.

Therefore, it is proposed to add an EP to multiple VPPs and make a VPP cluster. This EP is triggered by the power imbalance due to the failures to trade in the electricity markets and thus failure to meet the demand or failure to fulfill its trade contracts. The VPP cluster was developed, simulated, and analyzed. It was proven that the EP and the idea of a VPP cluster was able to mitigate multiple failures for multiple VPPs in the cluster effectively. Therefore, the proposed VPP cluster was found successful maintaining the power balance at the hours of failure. The VPP cluster comprises all the aforementioned ideas such as the risk consideration through the use of CVaR, piecewise linear function

representaion through a set of constraints to represent the conventional generator operational cost, sequential ARIMA, WDU, flexible demand, ESS, RES, conventional generator, reliability constriants, and of course an energy pool. It is worth noting that though the control scheme considered is central where the VPP operator is in charge of the operation of all the units within, the WDU was considered to be working on its own objective independently from the VPP. Eventhough the WDU is part of the VPP, it was allowed to optimize its own objective converting the control scheme from centralized to comprehensive as it is a load that has its own load which is the water demand.

Table 8-1 Contributions

Proposed Objective	Result
Construct a comprehensive VPP model containing dispatchable and non- dispatchable source	Model Developed
Formulate a multi-objective optimization problem	A multi-objective optimization problem was designed
Incorporate a WDU as a specific demand	A WDU has been designed and incorporated due to its high importance in countries like Saudi Arabia that rely on desalination and due to its importance as a virtual storage unit

Proposed Objective	Result
To propose a sequential ARIMA model for RT market for higher accuracy	The model has been developed and proven its efficiency in increasing the prediction accuracy
The comprehensive model shall participate in both the DA and RT markets	The simulation and results have been done on the two markets
Design a SOS2 model and compare its speed to set-of-constraints model for evaluation of the most computationally effective model for conventional generator piecewise linear function approximation	SOS2 model has been designed and tested and it has been proven that the set-of-constraints model is faster
To propose, construct, and evaluate a reliability model that makes the VPP immune to failure of power balance	A newly proposed model for reliability against power balance failures has been designed and it has proven its effectiveness in increasing the system reliability
To propose, construct, and evaluate a VPP cluster that incorporates an EP making a newly developed concept in VPP modelling	The model has been developed and it has proven its efficiency in making the system much more robust against failures

8.2 Future Work

As possible expansion to this work, a more detailed model could be considered by the inclusion or the modifications of some constraints. For example, the minimum up time and minimum down time of the conventional generator could be considered. This will lead to the need for a bigger simulation scope, more than 24 hours, in order to have a deeper insight of such modifications. Also, the lines may not be assumed lossless. The operational and maintenance costs of some components could be considered as well. Another important market is the ancillary services market which the VPP could participate into. Fully comprehensive control scheme could be simulated in addition to a distributed control scheme and compared to the centralized one.

The WDU can be studied under various scenarios such as a flat generation profile which will require different sizing and some modifications to the WDU to be suitable for this task. The WDU considered for this research had a specific water demand profile ranging from 700 m³ to 7000 m³ on the same day but at different hours. However, the tank had water charge/discharge rate of only 500 m³ which cannot work on flattening the water generation profile. This is in addition to the fact that the water demand profile is also fixed which can be made flexible. Other objectives could be added as well through the use of epsilon constraints and lexicographic optimization. The multiple VPPs of the same VPP cluster could even be made to interact with each other.

APPENDIX A

INPUT DATA AND PARAMETERS

A.1 Input Data

This appendix contains the input data used for the simulations.

Table A-1 Network data, [169]

Line	From	To	Capacity [MW]	Reactance (Ω)	Susceptance (S)
1	1	2	250	0.0281	35.5872
2	1	4	150	0.0304	32.8947
3	1	5	400	0.0064	156.2500
4	2	3	350	0.0108	92.5926
5	3	4	240	0.0297	33.6700
6	4	5	240	0.0297	33.6700

Table A-2 Demand data, [169]

Demand	$\underline{E}_d^D$ [MWh]	$\bar{P}_{dt}^D$ [MW]	$R_d^{D,U}$ $\left[\frac{\text{MW}}{\text{h}}\right]$	$-R_d^{D,D}$ $\left[\frac{\text{MW}}{\text{h}}\right]$	p_{do}^D [MW]
1	100	10	6	6	6
2	100	10	6	6	6
3	500	70	40	40	30
4	600	70	45	45	26
5	1200	150	100	100	78
6	1000	150	90	90	79
7	1500	200	110	110	89

Table A-3 Demand minimum, [169]

Time	$\underline{P}_{1t}^D$	$\underline{P}_{2t}^D$	$\underline{P}_{3t}^D$	$\underline{P}_{4t}^D$	$\underline{P}_{5t}^D$	$\underline{P}_{6t}^D$	$\underline{P}_{7t}^D$
h	[MW]	[MW]	[MW]	[MW]	[MW]	[MW]	[MW]
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	10	20	20
8	0	0	0	0	10	20	20
9	0	0	0	0	10	20	20
10	0	0	0	0	10	20	20
11	0	0	0	0	10	20	20
12	0	0	0	0	10	20	20
13	0	0	0	0	10	20	20
14	0	0	0	0	20	40	40
15	0	0	0	0	20	40	40
16	1	1	2	2	20	40	40
17	1	1	2	2	20	40	40
18	1	1	2	2	20	40	40

Time	$\underline{P}_{1t}^D$	$\underline{P}_{2t}^D$	$\underline{P}_{3t}^D$	$\underline{P}_{4t}^D$	$\underline{P}_{5t}^D$	$\underline{P}_{6t}^D$	$\underline{P}_{7t}^D$
19	1	1	2	2	20	40	40
20	1	1	2	2	20	40	40
21	1	1	2	2	20	40	40
22	1	1	2	2	10	20	20
23	1	1	2	2	10	20	20
24	0	0	0	0	0	0	0

Table A-4 Utility data, [169]

Demand	Load [MW]	Utility [\$ /MWh]
1	2.5,2.5,2.5,2.5	50,49,38,37
2	2.5,2.5,2.5,2.5	51,50,38,37
3	17.5,17.5,17.5,17.5	57,55,50,46
4	17.5,17.5,17.5,17.5	57,54,49,45
5	37.5,37.5,37.5,37.5	63,58,55,53
6	37.5,37.5,37.5,37.5	64,59,56,54
7	50,50,50,50	61,57,54,51

Table A-5 Hourly utility data 1

Hour	Demand	1				2				3			
	Load #	1	2	3	4	5	6	7	8	9	10	11	12
	Load (MW)	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	17.5	17.5	17.5	17.5
	Base Utility	50	49	38	37	51	50	38	37	57	55	50	46
1	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
2	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
3	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
4	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
5	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
6	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
7	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
8	Utility (\$/MWh)	40	39.2	30.4	29.6	40.8	40	30.4	29.6	45.6	44	40	36.8
9	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
10	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
11	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
12	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
13	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
14	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
15	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
16	Utility (\$/MWh)	50	49	38	37	51	50	38	37	57	55	50	46
17	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2
18	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2

Hour	Demand	1				2				3			
	Load #	1	2	3	4	5	6	7	8	9	10	11	12
	Load (MW)	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	17.5	17.5	17.5	17.5
	Base Utility	50	49	38	37	51	50	38	37	57	55	50	46
19	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2
20	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2
21	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2
22	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2
23	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2
24	Utility (\$/MWh)	60	58.8	45.6	44.4	61.2	60	45.6	44.4	68.4	66	60	55.2

Table A-6 Hourly utility data 2

Hour	Demand	4				5			
	Load #	13	14	15	16	17	18	19	20
	Load (MW)	17.5	17.5	17.5	17.5	37.5	37.5	37.5	37.5
	Base Utility	57	54	49	45	63	58	55	53
1	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
2	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
3	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
4	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
5	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
6	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
7	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
8	Utility (\$/MWh)	45.6	43.2	39.2	36	69.3	63.8	60.5	58.3
9	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
10	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
11	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
12	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
13	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
14	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
15	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
16	Utility (\$/MWh)	57	54	49	45	56.7	52.2	49.5	47.7
17	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53
18	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53
19	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53
20	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53
21	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53
22	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53
23	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53
24	Utility (\$/MWh)	68.4	64.8	58.8	54	63	58	55	53

Table A-7 Hourly utility data 3

Hour	Demand	6				7			
	Load #	21	22	23	24	25	26	27	28
	Load (MW)	37.5	37.5	37.5	37.5	50	50	50	50
	Base Utility	64	59	56	54	61	57	54	51
1	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
2	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
3	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
4	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
5	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
6	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
7	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
8	Utility (\$/MWh)	70.4	64.9	61.6	59.4	67.1	62.7	59.4	56.1
9	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
10	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
11	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
12	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
13	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
14	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
15	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
16	Utility (\$/MWh)	57.6	53.1	50.4	48.6	54.9	51.3	48.6	45.9
17	Utility (\$/MWh)	64	59	56	54	61	57	54	51
18	Utility (\$/MWh)	64	59	56	54	61	57	54	51
19	Utility (\$/MWh)	64	59	56	54	61	57	54	51
20	Utility (\$/MWh)	64	59	56	54	61	57	54	51
21	Utility (\$/MWh)	64	59	56	54	61	57	54	51
22	Utility (\$/MWh)	64	59	56	54	61	57	54	51
23	Utility (\$/MWh)	64	59	56	54	61	57	54	51
24	Utility (\$/MWh)	64	59	56	54	61	57	54	51

Table A-8 Storage data

Capacity	200 MWh
Initial Energy	200 MWh
Charging/ discharging efficiency	90%/90%
Maximum charge power	100 MW
Maximum discharge power	100 MW

Table A-9 Main grid and market data

Max. power exchange with main grid from/to	400 MW/ 400 MW
Max. power sold to the Day-ahead and real-time markets	300 MW
Max. power purchased from the Day- ahead and real-time markets	200 MW

Table A-10 Conventional generator data

Startup cost	1500 \$/h
Shut down cost	100 \$/h
Maximum production level	294 MW
Minimum production level	112 MW
Ramp up rate	60 MW/h
Ramp down rate	50 MW/h
Initial status	off
Initial power output	0 MW
Fixed production cost	824 \$/h
Startup ramp limit	170 MW/h
Shut down ramp limit	160 MW/h
Minimum up time	4 h
Minimum down time	4 h

Table A-11 Conventional generator variable cost

Block #	Cost Slope (\$/MWh)	Power (MW)
1	35.5	130
2	36.5	148
3	38	166
4	39	184
5	40.5	202
6	42	220
7	43	238
8	44.5	256
9	46	274
10	46.5	294

Table A-12 Wind Power scenarios

Hour	Scenario 1 (MW)	Scenario 2 (MW)	Scenario 3 (MW)	Scenario 4 (MW)	Scenario 5 (MW)
1	0.04	0.00	0.00	0.00	0.00
2	0.19	0.00	0.03	0.00	0.02
3	0.58	0.11	0.57	0.51	0.18
4	0.61	0.13	0.52	0.39	0.25
5	0.20	0.13	0.19	0.10	0.04
6	0.07	0.11	0.10	0.07	0.06
7	0.00	0.01	0.02	0.00	0.03
8	0.05	0.13	0.15	0.54	0.15
9	0.05	0.06	0.06	0.71	0.12
10	0.50	0.18	0.81	2.31	0.95
11	0.26	0.08	0.80	1.77	0.31
12	0.03	0.01	0.16	1.04	0.09
13	0.01	0.00	0.19	1.05	0.07
14	0.10	0.00	0.39	1.59	0.15
15	0.09	0.00	0.32	1.14	0.09
16	0.27	0.01	0.39	0.78	0.10

Hour	Scenario 1 (MW)	Scenario 2 (MW)	Scenario 3 (MW)	Scenario 4 (MW)	Scenario 5 (MW)
17	0.09	0.01	0.35	0.86	0.23
18	0.04	0.07	0.20	0.71	0.07
19	0.07	0.06	0.30	1.42	0.13
20	0.05	0.01	0.84	3.89	0.23
21	0.10	0.15	1.40	5.55	0.82
22	0.00	0.01	0.63	3.01	0.38
23	0.01	0.03	1.21	2.69	0.61
24	0.05	0.05	0.84	3.58	0.67

Table A-13 Actual DA market prices

Hour	Actual Lambda DA (\$/MWh)
1	33.72
2	29.88
3	28.94
4	27.94
5	28.4
6	31.79
7	36.9
8	38.03
9	39.12
10	41.16
11	43.7
12	45.64
13	48.55
14	48.42
15	45.67
16	47.95
17	48.1
18	48.13
19	47.41
20	43.95
21	45.66
22	42.32
23	36.65
24	34.04

Table A-14 DA market prices scenarios

Hour	Scenario 1 (\$/MWh)	Scenario 2 (\$/MWh)	Scenario 3 (\$/MWh)	Scenario 4 (\$/MWh)	Scenario 5 (\$/MWh)
1	35.74	36.09	35.74	35.99	35.28
2	35.19	35.26	34.88	35.54	35.11
3	33.84	33.59	33.95	34.16	33.62
4	33.15	32.98	32.69	33.33	32.78
5	33.08	32.91	32.96	33.01	33.31
6	33.42	33.16	33.11	33.12	33.57
7	34.09	33.76	34.25	33.93	34.05
8	37.12	36.73	36.90	37.72	37.60
9	39.76	39.06	39.33	39.93	40.12
10	42.80	42.06	42.48	43.44	43.53
11	44.70	43.96	44.34	44.87	45.28
12	45.29	45.14	45.12	45.81	46.27
13	45.81	44.92	45.65	46.08	46.22
14	46.22	45.59	46.01	46.58	46.78
15	45.59	45.16	45.30	45.64	46.04
16	47.04	46.24	46.98	47.24	47.49
17	48.15	47.44	47.63	48.17	48.44
18	46.94	46.84	46.50	47.07	47.26
19	42.70	42.61	42.55	43.54	43.29
20	42.94	43.40	43.29	43.68	43.32
21	49.86	50.03	50.12	50.52	50.52
22	42.08	41.72	41.87	42.36	42.39
23	37.19	37.06	36.40	37.54	38.00
24	36.42	36.76	36.30	37.06	37.35

Table A-15 DA market scenarios parameters

Scenario	Probability
Number of WP scenarios	5
Probability of each scenario	0.2
Number of DA price scenarios	5
Probability of each scenario	0.2
Number of RT prices scenarios	5
Probability of each scenario	0.2
Total Number of scenarios	$5*5*5=125$
Probability of each scenario	$0.2*0.2*0.2=0.008$

Table A-16 Residual RT market prices Scenarios

Hour	Scenario 1 (\$/MWh)	Scenario 2 (\$/MWh)	Scenario 3 (\$/MWh)	Scenario 4 (\$/MWh)	Scenario 5 (\$/MWh)
1	4.63	3.16	0.93	3.03	3.56
2	0.43	3.78	-0.72	2.90	4.48
3	-4.39	0.15	-1.30	-4.72	4.23
4	7.19	6.39	2.72	1.28	4.04
5	13.92	9.36	6.18	1.25	5.20
6	5.77	3.51	0.20	-3.72	-1.26
7	7.95	3.90	8.86	3.23	8.38
8	8.12	4.83	3.64	1.51	5.95
9	6.78	6.95	0.58	4.62	4.57
10	5.89	5.35	-1.67	-1.40	3.45
11	3.53	-0.99	-4.39	-4.67	-2.95
12	-0.51	-4.44	-6.35	-6.22	-4.30
13	-2.39	2.05	-4.34	0.42	-5.29
14	-4.85	-2.96	-4.14	-1.45	-12.57
15	-6.79	-8.71	-3.67	0.74	-12.58
16	-7.43	-8.90	-10.05	-2.65	-14.22
17	-4.52	-7.62	-4.89	-5.57	-9.06
18	-2.69	-12.51	-7.08	-4.79	-8.87
19	-9.41	-15.63	-8.55	-9.69	-7.50
20	-6.46	-0.53	-5.14	-1.67	-3.61
21	-8.85	-4.26	-6.10	-3.34	-6.90
22	-9.41	-5.95	-5.43	-5.05	-7.48
23	-2.69	-2.68	2.92	-0.40	-0.17
24	-3.05	-3.58	-0.80	-2.40	-0.50

Table A-17 Actual wind power output

Hour	WP (MW)
t1	1.832401
t2	0.852928
t3	0
t4	0.691312
t5	0
t6	0
t7	0
t8	1.248419
t9	0.359618
t10	0
t11	5.707968

Hour	WP (MW)
t12	3.623629
t13	5.645126
t14	8.520023
t15	8.838736
t16	7.009819
t17	12.5091
t18	14.74199
t19	9.638999
t20	6.66968
t21	3.111116
t22	10.02581
t23	11.10124
t24	11.26059

Table A-18 Actual RT market prices

Hour	Price (\$/MWh)
t1	30.96
t2	30.15
t3	30.21
t4	30.39
t5	32.36
t6	32.07
t7	39.63
t8	35.51
t9	34.48
t10	34.79
t11	36.01
t12	44.69
t13	47.75
t14	40.52
t15	35.02
t16	34.92
t17	35.99
t18	49.49
t19	37.64
t20	43.24
t21	37.73
t22	34.37
t23	35.1
t24	35.09

Table A-19 RT market scenarios

Scenario	Probability
Number of WP scenarios	5
Probability of each scenario	0.2
Number of RT prices scenarios	5
Probability of each scenario	0.2
Total Number of scenarios	5*5=25
Probability of each scenario	0.2*0.2=0.04

Table A-20 Wind power scenarios, first hour

Hour	Scenario 1 (MW)	Scenario 2 (MW)	Scenario 3 (MW)	Scenario 4 (MW)	Scenario 5 (MW)
1	0.14	0.14	0.14	0.14	0.14
2	1.53	1.41	1.35	0.39	5.24
3	4.11	3.34	6.35	0.87	3.20
4	4.99	3.53	3.07	0.46	2.42
5	3.57	2.76	1.50	0.15	1.10
6	1.55	3.52	0.93	0.12	0.00
7	1.42	5.03	1.33	0.70	0.81
8	1.42	2.09	0.55	0.58	0.14
9	2.60	3.60	0.31	0.93	1.21
10	3.60	8.11	0.85	1.33	2.94
11	8.91	14.35	3.16	3.78	6.36
12	27.94	26.23	18.34	7.24	13.85
13	25.14	31.92	10.58	2.12	9.74
14	21.44	36.83	14.81	5.72	18.09
15	25.96	54.38	17.36	10.01	33.37
16	16.47	33.73	7.77	6.81	31.02
17	21.06	23.79	4.96	3.07	33.25
18	18.18	17.70	9.23	3.38	34.64
19	7.48	12.70	6.50	0.95	23.80
20	5.43	13.34	3.36	1.36	33.13
21	3.67	10.90	3.37	2.02	33.31
22	2.91	6.63	2.01	1.74	38.69
23	3.52	3.60	2.22	1.48	36.37
24	3.79	2.76	2.26	1.08	35.28

Table A-21 Residual based RT market prices scenarios, first hour

Hour	Scenario 1 (\$/MWh)	Scenario 2 (\$/MWh)	Scenario 3 (\$/MWh)	Scenario 4 (\$/MWh)	Scenario 5 (\$/MWh)
1	4.63	3.16	0.93	3.03	3.56
2	0.43	3.78	-0.72	2.90	4.48
3	-4.39	0.15	-1.30	-4.72	4.23
4	7.19	6.39	2.72	1.28	4.04
5	13.92	9.36	6.18	1.25	5.20
6	5.77	3.51	0.20	-3.72	-1.26
7	7.95	3.90	8.86	3.23	8.38
8	8.12	4.83	3.64	1.51	5.95
9	6.78	6.95	0.58	4.62	4.57
10	5.89	5.35	-1.67	-1.40	3.45
11	3.53	-0.99	-4.39	-4.67	-2.95
12	-0.51	-4.44	-6.35	-6.22	-4.30
13	-2.39	2.05	-4.34	0.42	-5.29
14	-4.85	-2.96	-4.14	-1.45	-12.57
15	-6.79	-8.71	-3.67	0.74	-12.58
16	-7.43	-8.90	-10.05	-2.65	-14.22
17	-4.52	-7.62	-4.89	-5.57	-9.06
18	-2.69	-12.51	-7.08	-4.79	-8.87
19	-9.41	-15.63	-8.55	-9.69	-7.50
20	-6.46	-0.53	-5.14	-1.67	-3.61
21	-8.85	-4.26	-6.10	-3.34	-6.90
22	-9.41	-5.95	-5.43	-5.05	-7.48
23	-2.69	-2.68	2.92	-0.40	-0.17
24	-3.05	-3.58	-0.80	-2.40	-0.50

Table A-22 Wind power scenarios, second hour

Hour	Scenario 1 (MW)	Scenario 2 (MW)	Scenario 3 (MW)	Scenario 4 (MW)	Scenario 5 (MW)
1	1.83	1.83	1.83	1.83	1.83
2	0.85	0.85	0.85	0.85	0.85
3	7.63	8.57	0.00	0.78	0.00
4	9.29	6.19	0.00	0.99	0.00
5	2.14	16.61	0.00	2.45	0.00
6	0.00	20.43	0.00	3.17	1.20
7	0.00	24.14	0.00	1.05	3.81
8	0.40	20.85	0.00	2.15	8.55

Hou r	Scenario 1 (MW)	Scenario 2 (MW)	Scenario 3 (MW)	Scenario 4 (MW)	Scenario 5 (MW)
9	4.55	20.80	0.00	4.69	8.80
10	11.00	12.11	0.00	10.50	6.52
11	8.85	6.53	0.00	10.24	6.70
12	4.77	6.21	0.00	8.16	3.71
13	3.40	25.01	2.71	13.01	6.20
14	0.00	23.42	2.81	16.27	8.71
15	0.00	19.18	0.15	15.93	14.32
16	1.48	18.76	1.85	18.38	7.14
17	2.04	15.47	0.00	10.95	4.82
18	5.03	13.13	0.00	5.85	0.00
19	5.98	8.04	1.15	12.82	0.00
20	11.15	11.44	0.00	13.58	0.00
21	14.34	15.24	0.00	16.53	0.00
22	16.15	5.03	0.00	23.51	0.00
23	17.48	9.67	0.00	17.41	0.00
24	19.37	9.62	0.00	8.01	0.00

Table A-23 Residual based RT market prices scenarios, second hour

Ho ur	Scenario 1 (\$/MWh)	Scenario 2 (\$/MWh)	Scenario 3 (\$/MWh)	Scenario 4 (\$/MWh)	Scenario 5 (\$/MWh)
1	30.96	30.96	30.96	30.96	30.96
2	26.67	30.30	28.85	25.76	28.87
3	26.57	29.49	32.50	28.03	31.25
4	30.90	30.70	34.30	31.65	35.00
5	34.69	36.27	34.98	33.71	40.28
6	33.87	37.10	37.39	34.41	42.88
7	44.66	45.27	43.34	44.35	44.80
8	46.31	46.75	44.45	47.96	49.47
9	40.33	39.28	37.31	39.53	36.58
10	44.14	48.81	44.77	46.48	41.01
11	39.66	43.60	36.34	42.55	35.41
12	35.69	40.66	29.04	34.06	32.58
13	36.15	39.53	30.47	37.62	33.86
14	32.89	36.36	30.16	34.86	28.92
15	33.60	39.51	37.39	44.04	33.42
16	30.60	40.43	39.36	40.96	33.80

Hour	Scenario 1 (\$/MWh)	Scenario 2 (\$/MWh)	Scenario 3 (\$/MWh)	Scenario 4 (\$/MWh)	Scenario 5 (\$/MWh)
17	35.22	29.80	35.69	33.38	29.81
18	42.24	35.33	36.86	40.41	37.07
19	42.84	36.24	39.58	41.63	46.15
20	45.22	43.38	43.73	40.13	45.91
21	39.44	36.79	40.41	34.52	36.10
22	36.49	35.30	37.82	31.28	35.87
23	31.86	36.77	35.01	30.53	31.68
24	23.46	30.61	27.73	26.58	22.35

Table A-24 Wind power scenarios, third hour

Hour	Scenario 1 (MW)	Scenario 2 (MW)	Scenario 3 (MW)	Scenario 4 (MW)	Scenario 5 (MW)
1	1.83	1.83	1.83	1.83	1.83
2	0.85	0.85	0.85	0.85	0.85
3	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	3.91	0.00
5	0.00	2.10	0.00	9.75	0.00
6	0.00	3.47	1.95	5.38	0.00
7	0.00	0.00	5.16	7.58	0.46
8	0.00	0.00	5.97	12.25	2.80
9	0.00	2.99	5.85	8.77	2.03
10	0.00	4.78	9.50	8.28	11.68
11	0.00	3.57	9.53	8.55	21.55
12	0.00	3.14	9.51	11.85	17.57
13	0.00	0.00	8.96	7.77	12.55
14	0.00	0.00	4.80	1.81	2.73
15	0.00	0.00	3.70	0.73	0.00
16	3.84	0.00	8.70	1.96	0.00
17	9.26	2.28	8.98	6.94	3.72
18	9.54	2.26	10.49	9.28	8.07
19	8.13	4.72	15.73	10.09	9.17
20	3.20	1.49	8.74	4.89	8.38
21	0.00	9.19	10.75	0.00	3.76
22	0.00	3.83	8.89	0.81	2.76
23	0.00	0.24	6.11	0.00	4.09
24	0.00	2.28	10.98	0.81	4.33

Table A-25 Residual based RT market prices scenarios, third hour

Hour	Scenario 1 (\$/MWh)	Scenario 2 (\$/MWh)	Scenario 3 (\$/MWh)	Scenario 4 (\$/MWh)	Scenario 5 (\$/MWh)
1	30.96	30.96	30.96	30.96	30.96
2	30.15	30.15	30.15	30.15	30.15
3	36.35	31.51	34.01	30.56	30.74
4	37.50	33.33	30.76	26.92	28.24
5	32.86	34.36	30.65	28.31	26.63
6	34.77	36.15	31.99	34.10	27.41
7	45.34	45.24	43.40	42.05	39.84
8	44.84	42.87	40.74	45.07	39.76
9	34.20	31.26	31.74	27.58	29.63
10	38.28	37.10	40.53	36.92	44.16
11	35.25	34.68	33.79	33.24	37.50
12	33.90	36.95	33.50	32.19	31.17
13	42.30	46.11	38.82	34.60	38.04
14	37.37	39.23	38.92	27.81	31.42
15	39.71	41.11	39.95	34.75	38.50
16	41.09	38.24	41.04	37.50	35.38
17	36.47	38.37	38.17	35.41	33.36
18	34.98	41.81	40.45	42.09	40.42
19	36.48	37.67	35.60	37.96	39.42
20	50.42	42.94	38.45	43.13	40.18
21	41.42	41.17	33.76	38.84	40.71
22	35.42	40.51	27.73	39.40	42.89
23	34.94	31.99	27.68	34.36	40.46
24	33.06	27.27	23.82	25.26	30.31

APPENDIX B

SIMULATION RESULTS

B.1 Simulation Results

This section contains some of the results obtained from simulations.

Table B-1 DA market scheduled power scenarios

	Scenario 1 (MW)	Scenario 2 (MW)	Scenario 3 (MW)	Scenario 4 (MW)	Scenario 5 (MW)
t1	-200	-200	-200	-200	-200
t2	-200	-200	-200	-200	-200
t3	300	300	300	300	300
t4	-200	-200	-200	-200	-200
t5	-200	-200	-200	-200	-200
t6	300	300	300	300	300
t7	-200	-200	-200	-200	-200
t8	-200	-200	-200	-200	-200
t9	-200	-200	-200	-200	-200
t10	-200	-200	-200	-200	-200
t11	300	300	300	300	300
t12	300	300	300	300	300
t13	300	300	300	300	300
t14	300	300	300	300	300
t15	300	300	300	300	300
t16	300	300	300	300	300
t17	300	300	300	300	300
t18	300	300	300	300	300
t19	300	300	300	300	300
t20	300	300	300	300	300
t21	300	300	300	300	300
t22	300	300	300	300	300
t23	300	300	300	300	300
t24	300	300	300	300	300

Table B-2 DA market scheduled prices scenarios

	Scenario 1 (\$/MWh)	Scenario 2 (\$/MWh)	Scenario 3 (\$/MWh)	Scenario 4 (\$/MWh)	Scenario 5 (\$/MWh)
t1	35.74	36.09	35.74	35.99	35.28
t2	35.19	35.26	34.88	35.54	35.11
t3	33.84	33.59	33.95	34.16	33.62
t4	33.15	32.98	32.69	33.33	32.78
t5	33.08	32.91	32.96	33.01	33.31
t6	33.42	33.16	33.11	33.12	33.57
t7	34.09	33.76	34.25	33.93	34.05
t8	37.12	36.73	36.90	37.72	37.60
t9	39.76	39.06	39.33	39.93	40.12
t10	42.80	42.06	42.48	43.44	43.53
t11	44.70	43.96	44.34	44.87	45.28
t12	45.29	45.14	45.12	45.81	46.27
t13	45.81	44.92	45.65	46.08	46.22
t14	46.22	45.59	46.01	46.58	46.78
t15	45.59	45.16	45.30	45.64	46.04
t16	47.04	46.24	46.98	47.24	47.49
t17	48.15	47.44	47.63	48.17	48.44
t18	46.94	46.84	46.50	47.07	47.26
t19	42.70	42.61	42.55	43.54	43.29
t20	42.94	43.40	43.29	43.68	43.32
t21	49.86	50.03	50.12	50.52	50.52
t22	42.08	41.72	41.87	42.36	42.39
t23	37.19	37.06	36.40	37.54	38.00
t24	36.42	36.76	36.30	37.06	37.35

Table B-3 RT market scheduled power scenarios, 1

	g1 (MW)	g2 (MW)	g3 (MW)	g4 (MW)	g5 (MW)
t3	-200	-200	-200	-200	-200
t6	-200	-200	-200	-200	-200
t7	-200	-200	-200	-200	-200
t8	-200	-200	-200	-200	-200
t11	-200	-200	-200	-200	-200
t12	-500	-500	-500	-500	-500
t13	-421.10	-408.10	-408.10	-408.10	-500
t14	-500	-500	-500	-500	-500
t15	-500	-500	-500	-500	-500
t16	-500	-500	-500	-500	-500

	g1 (MW)	g2 (MW)	g3 (MW)	g4 (MW)	g5 (MW)
t17	-500	-500	-500	-500	-500
t18	-500	-500	-500	-500	-500
t19	-500	-500	-500	-500	-500
t20	-500	-500	-500	-500	-500
t21	-200	-200	-200	-200	-200
t22	-500	-500	-500	-500	-500
t23	-500	-500	-500	-500	-500
t24	-200	-200	-200	-200	-200

Table B-4 RT market scheduled power scenarios, 2

	g6 (MW)	g7 (MW)	g8 (MW)	g9 (MW)	g10 (MW)
t3	-200	-200	-200	-200	-200
t6	-200	-200	-200	-200	-200
t7	-200	-200	-200	-200	-200
t8	-200	-200	-200	-200	-200
t11	-200	-200	-200	-200	-200
t12	-500	-500	-500	-500	-500
t13	-421.10	-408.10	-408.10	-408.10	-500
t14	-500	-500	-500	-500	-500
t15	-500	-500	-500	-500	-500
t16	-500	-500	-500	-500	-500
t17	-500	-500	-500	-500	-500
t18	-500	-500	-500	-500	-500
t19	-500	-500	-500	-500	-500
t20	-500	-500	-500	-500	-500
t21	-200	-200	-200	-200	-200
t22	-500	-500	-500	-500	-500
t23	-500	-500	-500	-500	-500
t24	-200	-200	-200	-200	-200

Table B-5 RT market scheduled power scenarios, 3

	g11 (MW)	g12 (MW)	g13 (MW)	g14 (MW)	g15 (MW)
t3	-200	-200	-200	-200	-200
t6	-200	-200	-200	-200	-200
t7	-200	-200	-200	-200	-200
t8	-200	-200	-200	-200	-200
t11	-200	-200	-200	-200	-200
t12	-500	-500	-500	-500	-500
t13	-421.11	-408.11	-408.11	-408.11	-500

	g11 (MW)	g12 (MW)	g13 (MW)	g14 (MW)	g15 (MW)
t14	-500	-500	-500	-500	-500
t15	-500	-500	-500	-500	-500
t16	-500	-500	-500	-500	-500
t17	-500	-500	-500	-500	-500
t18	-500	-500	-500	-500	-500
t19	-500	-500	-500	-500	-500
t20	-500	-500	-500	-500	-500
t21	-200	-200	-200	-200	-200
t22	-500	-500	-500	-500	-500
t23	-500	-500	-500	-500	-500
t24	-200	-200	-200	-200	-200

Table B-6 RT market scheduled power scenarios, 4

	g16 (MW)	g17 (MW)	g18 (MW)	g19 (MW)	g20 (MW)
t3	-200	-200	-200	-200	-200
t6	-200	-200	-200	-200	-200
t7	-200	-200	-200	-200	-200
t8	-200	-200	-200	-200	-200
t11	-200	-200	-200	-200	-200
t12	-500	-500	-500	-500	-500
t13	-421.11	-408.11	-408.11	-408.11	-500
t14	-500	-500	-500	-500	-500
t15	-500	-500	-500	-500	-500
t16	-500	-500	-500	-500	-500
t17	-500	-500	-500	-500	-500
t18	-500	-500	-500	-500	-500
t19	-500	-500	-500	-500	-500
t20	-500	-500	-500	-500	-500
t21	-200	-200	-200	-200	-200
t22	-500	-500	-500	-500	-500
t23	-500	-500	-500	-500	-500
t24	-200	-200	-200	-200	-200

Table B-7 RT market scheduled power scenarios, 5

	g21 (MW)	g22 (MW)	g23 (MW)	g24 (MW)	g25 (MW)
t3	-200	-200	-200	-200	-200
t6	-200	-200	-200	-200	-200
t7	-200	-200	-200	-200	-200
t8	-200	-200	-200	-200	-200

	g21 (MW)	g22 (MW)	g23 (MW)	g24 (MW)	g25 (MW)
t11	-200	-200	-200	-200	-200
t12	-500	-500	-500	-500	-500
t13	-421.11	-408.11	-408.11	-408.11	-500
t14	-500	-500	-500	-500	-500
t15	-500	-500	-500	-500	-500
t16	-500	-500	-500	-500	-500
t17	-500	-500	-500	-500	-500
t18	-500	-500	-500	-500	-500
t19	-500	-500	-500	-500	-500
t20	-500	-500	-500	-500	-500
t21	-200	-200	-200	-200	-200
t22	-500	-500	-500	-500	-500
t23	-500	-500	-500	-500	-500
t24	-200	-200	-200	-200	-200

Table B-8 RT market scheduled price scenarios, 1

	g1 (\$/MWh)	g2 (\$/MWh)	g3 (\$/MWh)	g4 (\$/MWh)	g5 (\$/MWh)
t1	30.50	30.85	33.55	35.01	33.27
t2	26.67	30.30	28.85	25.76	28.87
t3	36.35	31.51	34.01	30.56	30.74
t4	33.12	25.78	30.24	31.53	29.03
t5	29.99	28.32	31.05	33.52	36.22
t6	36.80	36.45	33.34	34.48	34.65
t7	36.94	41.42	43.62	41.96	36.20
t8	44.81	38.49	46.10	40.15	37.23
t9	35.82	30.20	30.50	28.34	34.43
t10	43.49	44.66	46.54	43.89	41.42
t11	34.58	33.20	31.84	37.57	34.13
t12	39.68	34.07	33.74	36.22	38.02
t13	49.91	50.32	50.32	50.33	47.64
t14	33.98	40.81	39.49	39.50	41.43
t15	36.92	40.20	46.68	35.13	40.41
t16	38.96	38.05	38.55	40.40	36.49
t17	29.27	39.73	35.65	28.04	30.52
t18	35.30	29.89	39.63	35.53	37.53
t19	50.65	51.17	50.39	45.95	47.83
t20	41.11	37.41	40.67	40.78	42.00
t21	37.74	37.58	40.21	39.68	38.47
t22	40.20	41.12	41.56	34.97	40.49
t23	28.99	29.73	33.12	25.90	32.19

	g1 (\$/MWh)	g2 (\$/MWh)	g3 (\$/MWh)	g4 (\$/MWh)	g5 (\$/MWh)
t24	24.63	25.77	25.86	25.05	29.53

Table B-9 RT market scheduled price scenarios, 2

	g6 (\$/MWh)	g7 (\$/MWh)	g8 (\$/MWh)	g9 (\$/MWh)	g10 (\$/MWh)
t1	30.50	30.85	33.55	35.01	33.27
t2	26.67	30.30	28.85	25.76	28.87
t3	36.35	31.51	34.01	30.56	30.74
t4	33.12	25.78	30.24	31.53	29.03
t5	29.99	28.32	31.05	33.52	36.22
t6	36.80	36.45	33.34	34.48	34.65
t7	36.94	41.42	43.62	41.96	36.20
t8	44.81	38.49	46.10	40.15	37.23
t9	35.82	30.20	30.50	28.34	34.43
t10	43.49	44.66	46.54	43.89	41.42
t11	34.58	33.20	31.84	37.57	34.13
t12	39.68	34.07	33.74	36.22	38.02
t13	49.91	50.32	50.32	50.33	47.64
t14	33.98	40.81	39.49	39.50	41.43
t15	36.92	40.20	46.68	35.13	40.41
t16	38.96	38.05	38.55	40.40	36.49
t17	29.27	39.73	35.65	28.04	30.52
t18	35.30	29.89	39.63	35.53	37.53
t19	50.65	51.17	50.39	45.95	47.83
t20	41.11	37.41	40.67	40.78	42.00
t21	37.74	37.58	40.21	39.68	38.47
t22	40.20	41.12	41.56	34.97	40.49
t23	28.99	29.73	33.12	25.90	32.19
t24	24.63	25.77	25.86	25.05	29.53

Table B-10 RT market scheduled price scenarios, 3

	g11 (\$/MWh)	g12 (\$/MWh)	g13 (\$/MWh)	g14 (\$/MWh)	g15 (\$/MWh)
t1	30.50	30.85	33.55	35.01	33.27
t2	26.67	30.30	28.85	25.76	28.87
t3	36.35	31.51	34.01	30.56	30.74
t4	33.12	25.78	30.24	31.53	29.03
t5	29.99	28.32	31.05	33.52	36.22
t6	36.80	36.45	33.34	34.48	34.65
t7	36.94	41.42	43.62	41.96	36.20
t8	44.81	38.49	46.10	40.15	37.23

	g11 (\$/MWh)	g12 (\$/MWh)	g13 (\$/MWh)	g14 (\$/MWh)	g15 (\$/MWh)
t9	35.82	30.20	30.50	28.34	34.43
t10	43.49	44.66	46.54	43.89	41.42
t11	34.58	33.20	31.84	37.57	34.13
t12	39.68	34.07	33.74	36.22	38.02
t13	49.91	50.32	50.32	50.33	47.64
t14	33.98	40.81	39.49	39.50	41.43
t15	36.92	40.20	46.68	35.13	40.41
t16	38.96	38.05	38.55	40.40	36.49
t17	29.27	39.73	35.65	28.04	30.52
t18	35.30	29.89	39.63	35.53	37.53
t19	50.65	51.17	50.39	45.95	47.83
t20	41.11	37.41	40.67	40.78	42.00
t21	37.74	37.58	40.21	39.68	38.47
t22	40.20	41.12	41.56	34.97	40.49
t23	28.99	29.73	33.12	25.90	32.19
t24	24.63	25.77	25.86	25.05	29.53

Table B-11 RT market scheduled price scenarios, 4

	g16 (\$/MWh)	g17 (\$/MWh)	g18 (\$/MWh)	g19 (\$/MWh)	g20 (\$/MWh)
t1	30.50	30.85	33.55	35.01	33.27
t2	26.67	30.30	28.85	25.76	28.87
t3	36.35	31.51	34.01	30.56	30.74
t4	33.12	25.78	30.24	31.53	29.03
t5	29.99	28.32	31.05	33.52	36.22
t6	36.80	36.45	33.34	34.48	34.65
t7	36.94	41.42	43.62	41.96	36.20
t8	44.81	38.49	46.10	40.15	37.23
t9	35.82	30.20	30.50	28.34	34.43
t10	43.49	44.66	46.54	43.89	41.42
t11	34.58	33.20	31.84	37.57	34.13
t12	39.68	34.07	33.74	36.22	38.02
t13	49.91	50.32	50.32	50.33	47.64
t14	33.98	40.81	39.49	39.50	41.43
t15	36.92	40.20	46.68	35.13	40.41
t16	38.96	38.05	38.55	40.40	36.49
t17	29.27	39.73	35.65	28.04	30.52
t18	35.30	29.89	39.63	35.53	37.53
t19	50.65	51.17	50.39	45.95	47.83
t20	41.11	37.41	40.67	40.78	42.00
t21	37.74	37.58	40.21	39.68	38.47

	g16 (\$/MWh)	g17 (\$/MWh)	g18 (\$/MWh)	g19 (\$/MWh)	g20 (\$/MWh)
t22	40.20	41.12	41.56	34.97	40.49
t23	28.99	29.73	33.12	25.90	32.19
t24	24.63	25.77	25.86	25.05	29.53

Table B-12 RT market scheduled price scenarios, 5

	g21 (\$/MWh)	g22 (\$/MWh)	g23 (\$/MWh)	g24 (\$/MWh)	g25 (\$/MWh)
t1	30.50	30.85	33.55	35.01	33.27
t2	26.67	30.30	28.85	25.76	28.87
t3	36.35	31.51	34.01	30.56	30.74
t4	33.12	25.78	30.24	31.53	29.03
t5	29.99	28.32	31.05	33.52	36.22
t6	36.80	36.45	33.34	34.48	34.65
t7	36.94	41.42	43.62	41.96	36.20
t8	44.81	38.49	46.10	40.15	37.23
t9	35.82	30.20	30.50	28.34	34.43
t10	43.49	44.66	46.54	43.89	41.42
t11	34.58	33.20	31.84	37.57	34.13
t12	39.68	34.07	33.74	36.22	38.02
t13	49.91	50.32	50.32	50.33	47.64
t14	33.98	40.81	39.49	39.50	41.43
t15	36.92	40.20	46.68	35.13	40.41
t16	38.96	38.05	38.55	40.40	36.49
t17	29.27	39.73	35.65	28.04	30.52
t18	35.30	29.89	39.63	35.53	37.53
t19	50.65	51.17	50.39	45.95	47.83
t20	41.11	37.41	40.67	40.78	42.00
t21	37.74	37.58	40.21	39.68	38.47
t22	40.20	41.12	41.56	34.97	40.49
t23	28.99	29.73	33.12	25.90	32.19
t24	24.63	25.77	25.86	25.05	29.53

Table B-13 Demand bus 1

Hour	L1 (MW)	L2 (MW)	L3 (MW)	L4 (MW)
t1				
t2				
t3				
t4				
t5				
t6				

Hour	L1 (MW)	L2 (MW)	L3 (MW)	L4 (MW)
t7				
t8				
t9	1.5	1.5		
t10	2.5	2.5	0.33	
t11	2.5	2.5	1.54	0.5
t12	2.5	2.5	0.63	2
t13	2.5	1		0.5
t14	2.5	2.5		
t15	2.5	2.5	1.5	1
t16	2.5	2.5	1	1
t17	2.5	2.5	2.5	2.5
t18	2.5	2.5	2.5	2.5
t19	2.5	2.5	2.5	2.5
t20	2.5	2.5	2.5	2.5
t21	2.5	2.5	2.5	2.5
t22	2.5	2.5	2.5	2.5
t23	2.5	2.5	2.5	2.5
t24	1	1	2.5	2.5

Table B-14 Demand bus 2

Hour	L5 (MW)	L6 (MW)	L7 (MW)	L8 (MW)
t1				
t2				
t3				
t4				
t5				
t6				
t7				
t8				
t9	1.5	1.5		
t10	2.5	2.5		
t11	2.5	2.5		0.5
t12	2.5	2.5	1.5	2
t13	2.5	2.5		0.5
t14	2.5	2.5	0.5	0.5
t15	2.5	2.5	2	0.5
t16	2.5	2.5	1	1
t17	2.5	2.5	2.5	2.5
t18	2.5	2.5	2.5	2.5
t19	2.5	2.5	2.5	2.5

Hour	L5 (MW)	L6 (MW)	L7 (MW)	L8 (MW)
t20	2.5	2.5	2.5	2.5
t21	2.5	2.5	2.5	2.5
t22	2.5	2.5	2.5	2.5
t23	2.5	2.5	2.5	2.5
t24	2.5	1	2.5	2.5

Table B-15 Demand bus 3

	L9 (MW)	L10 (MW)	L11 (MW)	L12 (MW)	L13 (MW)	L14 (MW)	L15 (MW)	L16 (MW)
t1								
t2								
t3								
t4								
t5								
t6								
t7								
t8	7.5				5.25			
t9	17.5	10	10		16.50	11.25	11.25	
t10	17.5	17.5	17.5		17.5	17.5	17.5	
t11	17.5	17.5	17.5		17.5	17.5	17.5	
t12	17.5	17.5	17.5		17.5	17.5	17.5	3.75
t13	17.5	17.5	17.5		17.5	17.5	6.25	
t14	17.5	17.5	17.5		17.5	17.5	17.5	
t15	17.5	17.5	17.5		17.5	17.5	17.5	
t16	17.5	17.5	17.5	0.5	17.5	17.5	17.5	6.25
t17	17.5	17.5	17.5	10.5	17.5	17.5	17.5	17.5
t18	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5
t19	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5
t20	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5
t21	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5
t22	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5
t23	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5
t24	17.5	17.5	7.5	9	17.5	17.5	6.25	17.5

Table B-16 Demand bus 4

	L17 (MW)	L18 (MW)	L19 (MW)	L20 (MW)	L21 (MW)	L22 (MW)	L23 (MW)	L24 (MW)
t1	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5
t2	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5
t3	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5

	L17 (MW)	L18 (MW)	L19 (MW)	L20 (MW)	L21 (MW)	L22 (MW)	L23 (MW)	L24 (MW)
t4	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5
t5	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5
t6	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5
t7	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5
t8	37.5	37.5	37.5	37.5	37.5	37.5	37.5	37.5
t9	37.5	37.5	37.5	12.5	37.5	37.5	37.5	27.5
t1 0	37.5	37.5	37.5	2.5	37.5	37.5	37.5	5
t1 1	37.5	37.5	37.5	2.5	37.5	37.5	37.5	27.17
t1 2	37.5	37.5	37.5	2.5	37.5	37.5	37.5	15
t1 3	37.5	37.5	12.5	2.5	37.5	37.5	37.5	5
t1 4	37.5	37.5	37.5	5	37.5	37.5	37.5	27.5
t1 5	37.5	37.5	37.5	5	37.5	37.5	37.5	32.5
t1 6	37.5	37.5	37.5	5	37.5	37.5	37.5	25.26
t1 7	37.5	37.5	31.01	5	37.5	37.5	37.5	10
t1 8	37.5	37.5	26.24	5	37.5	37.5	37.5	10
t1 9	37.5	37.5	21.14	5	37.5	37.5	37.5	10
t2 0	37.5	37.5	18.17	5	37.5	37.5	37.5	10
t2 1	37.5	37.5	14.61	5	37.5	37.5	37.5	10
t2 2	37.5	37.5	37.5	2.5	37.5	37.5	37.5	5
t2 3	37.5	37.5	37.5	2.5	37.5	37.5	37.5	7.60
t2 4	37.5	12.5	12.5		37.5	15	15	

Table B-17 Demand bus 4, continued

	L25 (MW)	L26 (MW)	L27 (MW)	L28 (MW)
t1	49.75	49.75	49.75	22.58
t2	50.00	50.00	50.00	50.00
t3	50.00	50.00	50.00	50.00
t4	50.00	50.00	50.00	45.54

	L25 (MW)	L26 (MW)	L27 (MW)	L28 (MW)
t5	50.00	50.00	50.00	44.00
t6	50.00	50.00	50.00	44.00
t7	50.00	50.00	50.00	44.00
t8	50.00	50.00	50.00	32.50
t9	50.00	50.00	41.86	5.00
t10	50.00	50.00	41.17	5.00
t11	50.00	50.00	22.50	5.00
t12	50.00	50.00	25.25	5.00
t13	50.00	50.00	5.00	5.00
t14	50.00	50.00	19.02	10.00
t15	50.00	50.00	10.34	10.00
t16	50.00	50.00	10.00	10.00
t17	50.00	50.00	10.00	10.00
t18	50.00	50.00	10.00	10.00
t19	50.00	50.00	10.00	10.00
t20	50.00	50.00	10.00	10.00
t21	50.00	50.00	10.00	10.00
t22	50.00	50.00	6.53	5.00
t23	50.00	50.00	5.00	5.00
t24	27.01	22.50		

Table B-18 DA market power

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
1	-200.00	-200.00	-200.00
2	-200.00	-200.00	-200.00
3	300.00	0.00	0.00
4	-200.00	-200.00	-200.00
5	-200.00	-200.00	-200.00
6	-200.00	-200.00	0.00
7	-200.00	0.00	0.00
8	-200.00	0.00	0.00

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
9	-200.00	-200.00	-200.00
10	-200.00	-200.00	-200.00
11	-200.00	0.00	0.00
12	300.00	300.00	300.00
13	300.00	300.00	300.00
14	300.00	300.00	300.00
15	300.00	300.00	300.00
16	300.00	300.00	300.00
17	300.00	300.00	300.00
18	300.00	300.00	300.00
19	300.00	300.00	300.00
20	300.00	300.00	300.00
21	300.00	0.00	0.00
22	300.00	300.00	300.00
23	300.00	300.00	300.00
24	300.00	0.00	0.00

Table B-19 RT market power

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
1	0.00	0.00	0.00

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
2	0.00	0.00	0.00
3	-500.00	-200.00	-200.00
4	0.00	0.00	0.00
5	0.00	0.00	0.00
6	0.00	0.00	-200.00
7	0.00	-200.00	-200.00
8	0.00	-200.00	-200.00
9	0.00	0.00	0.00
10	0.00	0.00	0.00
11	0.00	-200.00	-200.00
12	0.00	0.00	0.00
13	-426.73	-424.73	-421.10
14	0.00	-500.00	-500.00
15	-500.00	-500.00	-500.00
16	-500.00	-500.00	-500.00
17	0.00	-500.00	-500.00
18	0.00	0.00	0.00
19	-500.00	-500.00	-500.00
20	0.00	0.00	0.00
21	-500.00	-200.00	-200.00
22	-500.00	-500.00	-500.00

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
23	0.00	0.00	0.00
24	0.00	0.00	0.00

Table B-20 Total demand

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
1	465.93	471.83	471.83
2	494.18	500.00	500.00
3	490.00	498.14	500.00
4	500.00	494.69	495.54
5	500.00	496.71	494.00
6	499.27	494.00	494.00
7	500.00	494.00	494.00
8	495.25	495.25	495.25
9	494.36	494.36	494.36
10	494.00	494.00	494.00
11	499.71	499.71	499.71
12	497.62	497.62	497.62
13	426.37	424.37	420.75
14	502.52	502.52	502.52
15	502.84	502.84	502.84

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
16	501.01	501.01	501.01
17	506.51	506.51	506.51
18	508.74	508.74	508.74
19	503.64	503.64	503.64
20	500.67	500.67	500.67
21	497.11	497.11	497.11
22	504.03	504.03	504.03
23	505.10	505.10	505.10
24	505.26	305.26	305.26

Table B-21 Total generation

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
1	265.93	271.83	271.83
2	294.18	300.00	300.00
3	290.00	298.14	300.00
4	300.00	294.69	295.54
5	300.00	296.71	294.00
6	299.27	294.00	294.00
7	300.00	294.00	294.00
8	295.25	295.25	295.25

	Deterministic (MW)	Stochastic (no risk) (MW)	Stochastic with risk (MW)
9	294.36	294.36	294.36
10	294.00	294.00	294.00
11	299.71	299.71	299.71
12	297.62	297.62	297.62
13	299.65	299.65	299.65
14	302.52	302.52	302.52
15	302.84	302.84	302.84
16	301.01	301.01	301.01
17	306.51	306.51	306.51
18	308.74	308.74	308.74
19	303.64	303.64	303.64
20	300.67	300.67	300.67
21	297.11	297.11	297.11
22	304.03	304.03	304.03
23	305.10	305.10	305.10
24	305.26	305.26	305.26

Table B-22 Profit

	Deterministic (\$)	Stochastic (no risk) (\$)	Stochastic with risk (\$)
DA market profit	113,301.00	104,435.00	110,793.00

	Deterministic (\$)	Stochastic (no risk) (\$)	Stochastic with risk (\$)
Utility and RT Profit	374732.9	323,152.90	316,735.82
Total Profit	488,033.92	427,587.90	427,528.82

References

- [1] General Secretariat of the European Council, "European Council (23 and 24 October 2014) Conclusions," 2014.
- [2] What is the Paris Agreement? UN Climate Change. [Online]. Available: <https://unfccc.int/process/the-paris-agreement/what-is-the-paris-agreement-0>
- [3] T. Ackermann and V. Knyazkin, "Interaction of distributed generation and the distribution network: Operation aspects" in *proc, in PES T&D Conf., Asia Pacic*, vol. 2, 2002, pp. 1357-1362
- [4] A. Satchwell, A. Mills, G. Barbose, R. Wiser, P. Cappers, and N. Darghouth, "Financial impacts of net-metered pv on utilities and ratepayers: a scoping study of two prototypical us utilities," 2014.
- [5] C. M. de Lagarde and F. Lantz, "How renewable production depresses electricity prices: Evidence from the German market," *Energy Policy*, vol. 117, pp. 263-277, 2018.
- [6] Y. Manabe, "Chapter 13 - Application of DERs in electricity market," in *Integration of Distributed Energy Resources in Power Systems*, T. Funabashi, Ed. Academic Press, 2016, pp. 295-302 [Online].
- [7] McKinsey, "Beyond the storm—value growth in the EU power sector.", 2014.
- [8] El Bakari, Khalil, J. M. A. Myrzik, and Wil L. Kling. "Prospects of a virtual power plant to control a cluster of distributed generation and renewable energy sources." In *2009 44th International Universities Power Engineering Conference (UPEC)*, pp. 1-5. IEEE, 2009.
- [9] Nikonowicz, Łukasz Bartosz, and Jarosław Milewski. "Virtual power plants-general review: structure, application and optimization." *Journal of Power Technologies* 92, no. 3 (2012): 135-149.
- [10] Koraki, Despina, and Kai Strunz. "Wind and solar power integration in electricity markets and distribution networks through service-centric virtual power plants." *IEEE Transactions on Power Systems* 33, no. 1 (2017): 473-485.
- [11] Zubo, Rana HA, Geev Mokryani, Haile-Selassie Rajamani, Jamshid Aghaei, Taher Niknam, and Prashant Pillai. "Operation and planning of distribution networks with integration of renewable distributed generators considering uncertainties: A review." *Renewable and Sustainable Energy Reviews* 72 (2017): 1177-1198.
- [12] Othman, M. M., Walid El-Khattam, Yasser G. Hegazy, and Almoataz Y. Abdelaziz. "Optimal placement and sizing of distributed generators in unbalanced distribution systems using supervised big bang-big crunch method." *IEEE Transactions on Power Systems* 30, no. 2 (2014): 911-919.
- [13] Kolenc, Mitja, Peter Nemček, Christoph Gutschi, Nermin Suljanović, and Matej Zajc. "Performance evaluation of a virtual power plant communication system providing ancillary services." *Electric Power Systems Research* 149 (2017): 46-54.
- [14] T. Development: 'WEB to energy: report of Landis + Gyr', 2010

- [15] Sučić, Stjepan, Sebastian Rohjans, and Wolfgang Mahnke. "Semantic smart grid services: Enabling a standards-compliant Internet of energy platform with IEC 61850 and OPC UA." In *Eurocon 2013*, pp. 1375-1382. IEEE, 2013.
- [16] Awerbuch, Shimon, and Alistair Preston, eds. *The virtual utility: Accounting, technology & competitive aspects of the emerging industry*. Vol. 26. Springer Science & Business Media, 2012.
- [17] Pudjianto, Danny, Charlotte Ramsay, and Goran Strbac. "Virtual power plant and system integration of distributed energy resources." *IET Renewable power generation* 1, no. 1 (2007): 10-16.
- [18] Othman, Mahmoud M., Y. Hegazy, and Almoataz Y. Abdelaziz. "A Review of virtual power plant definitions, components, framework and optimization." *International Electrical Engineering Journal* 6, no. 9 (2015): 2010-2024.
- [19] Wei, Yixuan, Xingxing Zhang, Yong Shi, Liang Xia, Song Pan, Jinshun Wu, Mengjie Han, and Xiaoyun Zhao. "A review of data-driven approaches for prediction and classification of building energy consumption." *Renewable and Sustainable Energy Reviews* 82 (2018): 1027-1047.
- [20] Nosratabadi, Seyyed Mostafa, Rahmat-Allah Hooshmand, and Eskandar Gholipour. "A comprehensive review on microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems." *Renewable and Sustainable Energy Reviews* 67 (2017): 341-363.
- [21] Ghavidel, Sahand, Li Li, Jamshid Aghaei, Tao Yu, and Jianguo Zhu. "A review on the virtual power plant: Components and operation systems." In *2016 IEEE International Conference on Power System Technology (POWERCON)*, pp. 1-6. IEEE, 2016.
- [22] You, Shi, Chresten Træholt, and Bjarne Poulsen. "A market-based virtual power plant." In *2009 International Conference on Clean Electrical Power*, pp. 460-465. IEEE, 2009.
- [23] Tabatabaee, Sajad, Seyed Saeedallah Mortazavi, and Taher Niknam. "Stochastic energy management of renewable micro-grids in the correlated environment using unscented transformation." *Energy* 109 (2016): 365-377.
- [24] Santodomingo, R., M. Uslar, A. Göring, M. Gottschalk, Lars Nordström, Arshad Saleem, and Moustafa Chenine. "SGAM-based methodology to analyse Smart Grid solutions in DISCERN European research project." In *2014 IEEE International Energy Conference (ENERGYCON)*, pp. 751-758. IEEE, 2014.
- [25] Lombardi, P., T. Sokolnikova, Z. Styczynski, and N. Voropai. "Virtual power plant management considering energy storage systems." *IFAC Proceedings Volumes* 45, no. 21 (2012): 132-137.
- [26] Othman, Mahmoud M., Y. G. Hegazy, and Almoataz Y. Abdelaziz. "Electrical energy management in unbalanced distribution networks using virtual power plant concept." *Electric Power Systems Research* 145 (2017): 157-165.
- [27] Kasaei, Mohammad Javad, Majid Gandomkar, and Javad Nikoukar. "Optimal management of renewable energy sources by virtual power plant." *Renewable Energy* 114 (2017): 1180-1188.

- [28] Lombardi, Pio, Michal Powalko, and Krzysztof Rudion. "Optimal operation of a virtual power plant." In 2009 IEEE Power & Energy Society General Meeting, pp. 1-6. IEEE, 2009.
- [29] Caldon, Roberto, A. Rossi Patria, and Roberto Turri. "Optimal control of a distribution system with a virtual power plant." Bulk power system dynamics and control, Cortina. d'Ampezzo, Italy (2004): 18.
- [30] Caldon, Roberto, A. Rossi Patria, and Roberto Turri. "Optimisation algorithm for a virtual power plant operation." In 39th International Universities Power Engineering Conference, 2004. UPEC 2004., vol. 3, pp. 1058-1062. IEEE, 2004.
- [31] Bahrami, Shahab, and Aras Sheikhi. "From demand response in smart grid toward integrated demand response in smart energy hub." IEEE Transactions on Smart Grid 7, no. 2 (2015): 650-658.
- [32] Sheikhi, Aras, Shahab Bahrami, and Ali Mohammad Ranjbar. "An autonomous demand response program for electricity and natural gas networks in smart energy hubs." Energy 89 (2015): 490-499.
- [33] Zhaoxia, Xiao, Nan Jiakai, Josep M. Guerrero, and Fang Hongwei. "Multiple time-scale optimization scheduling for islanded microgrids including PV, wind turbine, diesel generator and batteries." In IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society, pp. 2594-2599. IEEE, 2017.
- [34] Florez-Celis, Hector A., Carlos A. Ruiz-Zea, German D. Zapata-Madrigal, and Leon A. Martinez-Giraldo. "Maintenance scheduling for a power system operating assets using Petri nets integration with ant colony optimization." In 2016 IEEE Colombian Conference on Communications and Computing (COLCOM), pp. 1-6. IEEE, 2016.
- [35] Chen, S. X., Hoay Beng Gooi, and MingQiang Wang. "Sizing of energy storage for microgrids." IEEE Transactions on Smart Grid 3, no. 1 (2011): 142-151.
- [36] Li, Wei, Géza Joós, and Jean Bélanger. "Real-time simulation of a wind turbine generator coupled with a battery supercapacitor energy storage system." IEEE Transactions on Industrial Electronics 57, no. 4 (2009): 1137-1145.
- [37] Mashhour, Elaheh, and S. M. Moghaddas-Tafreshi. "A review on operation of micro grids and virtual power plants in the power markets." In 2009 2nd International Conference on Adaptive Science & Technology (ICAST), pp. 273-277. IEEE, 2009.
- [38] Skajaa, Anders, Kristian Edlund, and Juan M. Morales. "Intraday trading of wind energy." IEEE Transactions on Power Systems 30, no. 6 (2015): 3181-3189.
- [39] Lima, Ricardo M., Antonio J. Conejo, Sabique Langodan, Ibrahim Hoteit, and Omar M. Knio. "Risk-averse formulations and methods for a virtual power plant." Computers & Operations Research 96 (2018): 350-373.
- [40] Xin, Huanhai, Zehan Lu, Yun Liu, and Deqiang Gan. "A center-free control strategy for the coordination of multiple photovoltaic generators." IEEE Transactions on Smart Grid 5, no. 3 (2014): 1262-1269.
- [41] Abdelaziz, A. Y., Y. G. Hegazy, Walid El-Khattam, and M. M. Othman. "Virtual Power Plant: The Future of Power Delivery Systems." In European Workshop on Renewable Energy Systems, pp. 1-2.

- [42] Robu, Valentin, Georgios Chalkiadakis, Ramachandra Kota, Alex Rogers, and Nicholas R. Jennings. "Rewarding cooperative virtual power plant formation using scoring rules." *Energy* 117 (2016): 19-28.
- [43] Dabbagh, Saeed Rahmani, and Mohammad Kazem Sheikh-El-Eslami. "Risk assessment of virtual power plants offering in energy and reserve markets." *IEEE Transactions on Power Systems* 31, no. 5 (2015): 3572-3582.
- [44] Rahmani-Dabbagh, Saeed, and Mohammad Kazem Sheikh-El-Eslami. "A profit sharing scheme for distributed energy resources integrated into a virtual power plant." *Applied energy* 184 (2016): 313-328.
- [45] Shayegan-Rad, Ali, Ali Badri, and Ali Zangeneh. "Day-ahead scheduling of virtual power plant in joint energy and regulation reserve markets under uncertainties." *Energy* 121 (2017): 114-125.
- [46] Guo, Hongye, Qixin Chen, Qing Xia, Junliu Zhang, Ming Li, and Peng Zou. "Evaluating the impacts of VPPs on the joint energy and ancillary service markets equilibrium." In *2017 IEEE Power & Energy Society General Meeting*, pp. 1-5. IEEE, 2017.
- [47] Giuntoli, Marco, and Davide Poli. "Optimized thermal and electrical scheduling of a large scale virtual power plant in the presence of energy storages." *IEEE Transactions on Smart Grid* 4, no. 2 (2013): 942-955.
- [48] Zhao, Haoran, Qiuwei Wu, Shuju Hu, Honghua Xu, and Claus Nygaard Rasmussen. "Review of energy storage system for wind power integration support." *Applied energy* 137 (2015): 545-553.
- [49] Zhou, Bin, Xi Liu, Yijia Cao, Canbing Li, Chi Yung Chung, and Ka Wing Chan. "Optimal scheduling of virtual power plant with battery degradation cost." *IET Generation, Transmission & Distribution* 10, no. 3 (2016): 712-725.
- [50] He, Guannan, Qixin Chen, Panayiotis Moutis, Soumya Kar, and Jay F. Whitacre. "An intertemporal decision framework for electrochemical energy storage management." *Nature Energy* 3, no. 5 (2018): 404-412.
- [51] Kanakasabapathy, P., and K. Shanti Swarup. "Bidding strategy for pumped-storage plant in pool-based electricity market." *Energy conversion and Management* 51, no. 3 (2010): 572-579.
- [52] Hu, Junjie, Hugo Morais, Morten Lind, and Henrik W. Bindner. "Multi-agent based modeling for electric vehicle integration in a distribution network operation." *Electric Power Systems Research* 136 (2016): 341-351.
- [53] Moghaddam, Saeed Zolfaghari, and Tohid Akbari. "Network-constrained optimal bidding strategy of a plug-in electric vehicle aggregator: A stochastic/robust game theoretic approach." *Energy* 151 (2018): 478-489.
- [54] Baringo, Luis, and Raquel Sánchez Amaro. "A stochastic robust optimization approach for the bidding strategy of an electric vehicle aggregator." *Electric Power Systems Research* 146 (2017): 362-370.
- [55] Wang, Yao, Xin Ai, Zhongfu Tan, Lei Yan, and Shuting Liu. "Interactive dispatch modes and bidding strategy of multiple virtual power plants based on demand response and game theory." *IEEE Transactions on Smart Grid* 7, no. 1 (2015): 510-519.

- [56] Al-Awami, Ali T., Nemer A. Amleh, and Ammar M. Muqbel. "Optimal demand response bidding and pricing mechanism with fuzzy optimization: Application for a virtual power plant." *IEEE Transactions on Industry Applications* 53, no. 5 (2017): 5051-5061.
- [57] Ju, Liwei, Zhongfu Tan, Jinyun Yuan, Qingkun Tan, Huanhuan Li, and Fugui Dong. "A bi-level stochastic scheduling optimization model for a virtual power plant connected to a wind-photovoltaic-energy storage system considering the uncertainty and demand response." *Applied energy* 171 (2016): 184-199.
- [58] Caicedo, David, and Ashish Pandharipande. "Energy performance prediction of lighting systems." In *2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP)*, pp. 1-6. IEEE, 2016.
- [59] Nakayama, Kiyoshi, and Ratnesh Sharma. "Energy management systems with intelligent anomaly detection and prediction." In *2017 Resilience Week (RWS)*, pp. 24-29. IEEE, 2017.
- [60] Koutroulis, Eftichios. "5.17 energy management in wind energy systems." (2018): 707-741.
- [61] Niknam, Taher, Rasoul Azizipanah-Abarghooee, and Mohammad Rasoul Narimani. "An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation." *Applied Energy* 99 (2012): 455-470.
- [62] Simoes, Marcelo Godoy, Bimal K. Bose, and Ronald J. Spiegel. "Design and performance evaluation of a fuzzy-logic-based variable-speed wind generation system." *IEEE Transactions on Industry Applications* 33, no. 4 (1997): 956-965.
- [63] Zhang, Jun, Henry Shu-Hung Chung, and Wai-Lun Lo. "Clustering-based adaptive crossover and mutation probabilities for genetic algorithms." *IEEE Transactions on Evolutionary Computation* 11, no. 3 (2007): 326-335.
- [64] Denis, Boyarkin, Krupenev Dmitriy, Iakubovskiy Dmitriy, and Sidorov Denis. "Machine learning in electric power systems adequacy assessment using Monte-Carlo method." In *2017 International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON)*, pp. 201-205. IEEE, 2017.
- [65] Lei, Yang, and Alex Q. Huang. "Data center power distribution system reliability analysis tool based on Monte Carlo next event simulation method." In *2017 IEEE Energy Conversion Congress and Exposition (ECCE)*, pp. 2031-2035. IEEE, 2017.
- [66] Ghahderijani, Mohammad Moradi, S. Masoud Barakati, and Saeed Tavakoli. "Reliability evaluation of stand-alone hybrid microgrid using Sequential Monte Carlo Simulation." In *2012 Second Iranian Conference on Renewable Energy and Distributed Generation*, pp. 33-38. IEEE, 2012.
- [67] Bocklisch, Thilo. "Hybrid energy storage systems for renewable energy applications." *Energy Procedia* 73, no. 2015 (2015): 103-111.
- [68] Kocaman, Ayse Selin, Carlos Abad, Tara J. Troy, Woonghee Tim Huh, and Vijay Modi. "A stochastic model for a macroscale hybrid renewable energy system." *Renewable and Sustainable Energy Reviews* 54 (2016): 688-703.
- [69] Dawoud, Samir M., Xiangning Lin, and Merfat I. Okba. "Hybrid renewable microgrid optimization techniques: A review." *Renewable and Sustainable Energy Reviews* 82 (2018): 2039-2052.

- [70] Malik, Hasmat, and Sukumar Mishra. "Artificial neural network and empirical mode decomposition based imbalance fault diagnosis of wind turbine using TurbSim, FAST and Simulink." *IET Renewable Power Generation* 11, no. 6 (2016): 889-902.
- [71] You, Shi. "Developing virtual power plant for optimized distributed energy resources operation and integration." (2010).
- [72] Biswas, MA Rafe, Melvin D. Robinson, and Nelson Fumo. "Prediction of residential building energy consumption: A neural network approach." *Energy* 117 (2016): 84-92.
- [73] Eldhose, Elby K., and G. Jisha. "Active cluster node aggregation scheme in wireless sensor network using neural network." *Procedia Technology* 24 (2016): 1603-1608.
- [74] Rekik, Mouna, Zied Chtourou, Nathalie Mitton, and Ahmad Atieh. "Geographic routing protocol for the deployment of virtual power plant within the smart grid." *Sustainable Cities and Society* 25 (2016): 39-48.
- [75] Kumar, Shivendra, and Nidhi Singh Pal. "Ant colony optimization for less power consumption and fast charging of battery in solar grid system." In *2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON)*, pp. 244-249. IEEE, 2017.
- [76] Carrión, Miguel, and José M. Arroyo. "A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem." *IEEE Transactions on power systems* 21, no. 3 (2006): 1371-1378.
- [77] Narkhede, Mahesh S., S. Chatterji, and Smarajit Ghosh. "Multi objective optimal dispatch in a virtual power plant using genetic algorithm." In *2013 International Conference on Renewable Energy and Sustainable Energy (ICRESE)*, pp. 238-242. IEEE, 2013.
- [78] Eiben, Ágoston E., Robert Hinterding, and Zbigniew Michalewicz. "Parameter control in evolutionary algorithms." *IEEE Transactions on evolutionary computation* 3, no. 2 (1999): 124-141.
- [79] Wan, Jiashuang, and Fuyu Zhao. "Optimization of AP1000 power control system setpoints using genetic algorithm." *Progress in Nuclear Energy* 95 (2017): 23-32.
- [80] Mohammadi, Sirus, Soodabeh Soleymani, and Babak Mozafari. "Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices." *International Journal of Electrical Power & Energy Systems* 54 (2014): 525-535.
- [81] Senthilnath, J., S. N. Omkar, and V. Mani. "Clustering using firefly algorithm: performance study." *Swarm and Evolutionary Computation* 1, no. 3 (2011): 164-171.
- [82] Balachennaiah, P., and M. Suryakalavathi. "Notice of Retraction Fire-fly algorithm for the optimization of real power loss and voltage stability limit." In *2015 International Conference on Electrical, Electronics, Signals, Communication and Optimization (EESCO)*, pp. 1-7. IEEE, 2015.
- [83] Eteiba, M. B., Shimaa Barakat, M. M. Samy, and Wael Ismael Wahba. "Optimization of an off-grid PV/Biomass hybrid system with different battery technologies." *Sustainable cities and society* 40 (2018): 713-727.

- [84] Zhang, Changsheng, Dantong Ouyang, and Jiaxu Ning. "An artificial bee colony approach for clustering." *Expert systems with applications* 37, no. 7 (2010): 4761-4767.
- [85] Aydin, Doğan, Serdar Özyön, Celal Yaşar, and Tianjun Liao. "Artificial bee colony algorithm with dynamic population size to combined economic and emission dispatch problem." *International journal of electrical power & energy systems* 54 (2014): 144-153.
- [86] Shrivastava, Amit, Manisha Dubey, and Yogendra Kumar. "Design of interactive artificial bee colony based multiband power system stabilizers in multimachine power system." In *2013 international conference on control, automation, robotics and embedded systems (CARE)*, pp. 1-6. IEEE, 2013.
- [87] Abegaz, Brook W., and Satish M. Mahajan. "Optimal real-time integration control of a virtual power plant." In *2014 North American Power Symposium (NAPS)*, pp. 1-6. IEEE, 2014.
- [88] Zhu, Haibin, Dongning Liu, Siqin Zhang, Shaohua Teng, and Yu Zhu. "Solving the group multirole assignment problem by improving the ILOG approach." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 47, no. 12 (2016): 3418-3424.
- [89] Liu, Fang, and Zhiguang Zhou. "An improved QPSO algorithm and its application in the high-dimensional complex problems." *Chemometrics and Intelligent Laboratory Systems* 132 (2014): 82-90.
- [90] Hosseinneshad, Vahid, Mansour Rafiee, Mohammad Ahmadian, and Mohammad Taghi Ameli. "Species-based quantum particle swarm optimization for economic load dispatch." *International Journal of Electrical Power & Energy Systems* 63 (2014): 311-322.
- [91] Banerjee, Sumit, Koustav Dasgupta, and Chandan Kumar Chanda. "Short term hydro–wind–thermal scheduling based on particle swarm optimization technique." *International Journal of Electrical Power & Energy Systems* 81 (2016): 275-288.
- [92] Baziar, Aliasghar, and Abdollah Kavousi-Fard. "Considering uncertainty in the optimal energy management of renewable micro-grids including storage devices." *Renewable Energy* 59 (2013): 158-166.
- [93] Tchapda, Ghislain Yanick Gninkeu, Zenghui Wang, and Yanxia Sun. "Application of improved particle swarm optimization in economic dispatch of power system." In *2017 10th International Symposium on Computational Intelligence and Design (ISCID)*, vol. 2, pp. 500-503. IEEE, 2017.
- [94] Tungadio, D. H., B. P. Numbi, M. W. Siti, and Adisa A. Jimoh. "Particle swarm optimization for power system state estimation." *Neurocomputing* 148 (2015): 175-180.
- [95] Rahimiyan, Morteza, and Luis Baringo. "Strategic bidding for a virtual power plant in the day-ahead and real-time markets: A price-taker robust optimization approach." *IEEE Transactions on Power Systems* 31, no. 4 (2015): 2676-2687.
- [96] Zeng, Bo, and Long Zhao. "Solving two-stage robust optimization problems using a column-and-constraint generation method." *Operations Research Letters* 41, no. 5 (2013): 457-461.

- [97] Bertsimas, Dimitris, and Melvyn Sim. "Robust discrete optimization and network flows." *Mathematical programming* 98, no. 1 (2003): 49-71.
- [98] GAMS: Available at www.gams.com/ (2021).
- [99] ILOG CPLEX.: Available at www.ilog.com/products/cplex/ (2021).
- [100] Jiang, Ruiwei, Muhong Zhang, Guang Li, and Yongpei Guan. "Two-stage network constrained robust unit commitment problem." *European Journal of Operational Research* 234, no. 3 (2014): 751-762.
- [101] Floudas, Christodoulos A. *Nonlinear and mixed-integer optimization: fundamentals and applications*. Oxford University Press, 1995.
- [102] Werner, T. G., and R. Remberg. "Technical, economical and regulatory aspects of Virtual Power Plants." In *2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, pp. 2427-2433. IEEE, 2008.
- [103] Pandžić, Hrvoje, Igor Kuzle, and Tomislav Capuder. "Virtual power plant mid-term dispatch optimization." *Applied Energy* 101 (2013): 134-141.
- [104] Salmani, M. Amin, SM Moghaddas Tafreshi, and Hosein Salmani. "Operation optimization for a virtual power plant." In *2009 IEEE PES/IAS Conference on Sustainable Alternative Energy (SAE)*, pp. 1-6. IEEE, 2009.
- [105] Stott, Brian, and Eric Hobson. "Power system security control calculations using linear programming, Part I." *IEEE Transactions on Power Apparatus and Systems* 5 (1978): 1713-1720.
- [106] Khalesi, N., Nariman Rezaei, and M-R. Haghifam. "DG allocation with application of dynamic programming for loss reduction and reliability improvement." *International Journal of Electrical Power & Energy Systems* 33, no. 2 (2011): 288-295.
- [107] Aien, Morteza, Masoud Rashidinejad, and Mahmud Fotuhi-Firuzabad. "On possibilistic and probabilistic uncertainty assessment of power flow problem: A review and a new approach." *Renewable and Sustainable Energy Reviews* 37 (2014): 883-895.
- [108] Borges, Carmen LT, and Djalma M. Falcao. "Optimal distributed generation allocation for reliability, losses, and voltage improvement." *International Journal of Electrical Power & Energy Systems* 28, no. 6 (2006): 413-420.
- [109] Abdelaziz, Almoataz Y., Yasser G. Hegazy, Walid El-Khattam, and Mahmoud M. Othman. "Optimal planning of distributed generators in distribution networks using modified firefly method." *Electric Power Components and Systems* 43, no. 3 (2015): 320-333.
- [110] Li, Zuyi, and Mohammad Shahidehpour. "Security-constrained unit commitment for simultaneous clearing of energy and ancillary services markets." *IEEE transactions on power systems* 20, no. 2 (2005): 1079-1088.
- [111] Peik-Herfeh, Malahat, H. Seifi, and M. K. Sheikh-El-Eslami. "Decision making of a virtual power plant under uncertainties for bidding in a day-ahead market using point estimate method." *International Journal of Electrical Power & Energy Systems* 44, no. 1 (2013): 88-98.

- [112] Shabanzadeh, Morteza, Mohammad-Kazem Sheikh-El-Eslami, and Mahmoud-Reza Haghighi. "A medium-term coalition-forming model of heterogeneous DERs for a commercial virtual power plant." *Applied Energy* 169 (2016): 663-681.
- [113] Nezamabadi, Hossein, and Mehrdad Setayesh Nazar. "Arbitrage strategy of virtual power plants in energy, spinning reserve and reactive power markets." *IET Generation, Transmission & Distribution* 10, no. 3 (2016): 750-763.
- [114] Xu, Qianqiao, Ning Zhang, Chongqing Kang, Qing Xia, Dawei He, Chun Liu, Yuehui Huang, Lu Cheng, and Jianhua Bai. "A game theoretical pricing mechanism for multi-area spinning reserve trading considering wind power uncertainty." *IEEE Transactions on Power Systems* 31, no. 2 (2015): 1084-1095.
- [115] Raineri, Ricardo, S. Rios, and D. Schiele. "Technical and economic aspects of ancillary services markets in the electric power industry: an international comparison." *Energy policy* 34, no. 13 (2006): 1540-1555.
- [116] Tajeddini, Mohammad Amin, Ashkan Rahimi-Kian, and Alireza Soroudi. "Risk averse optimal operation of a virtual power plant using two stage stochastic programming." *Energy* 73 (2014): 958-967.
- [117] Aien, Morteza, Ali Hajebrahimi, and Mahmud Fotuhi-Firuzabad. "A comprehensive review on uncertainty modeling techniques in power system studies." *Renewable and Sustainable Energy Reviews* 57 (2016): 1077-1089.
- [118] Degeilh, Yannick, and George Gross. "Stochastic simulation of power systems with integrated intermittent renewable resources." *International Journal of Electrical Power & Energy Systems* 64 (2015): 542-550.
- [119] El-Khattam, Walid, Y. G. Hegazy, and M. M. A. Salama. "Investigating distributed generation systems performance using Monte Carlo simulation." *IEEE Transactions on Power Systems* 21, no. 2 (2006): 524-532.
- [120] Zio, Enrico, Maurizio Delfanti, L. Giorgi, Valeria Olivieri, and Giovanni Sansavini. "Monte Carlo simulation-based probabilistic assessment of DG penetration in medium voltage distribution networks." *International Journal of Electrical Power & Energy Systems* 64 (2015): 852-860.
- [121] Shafie-khah, Miadreza, Mohsen Parsa Moghaddam, Mohamad Kazem Sheikh-El-Eslami, and Mehdi Rahmani-Andebili. "Modeling of interactions between market regulations and behavior of plug-in electric vehicle aggregators in a virtual power market environment." *Energy* 40, no. 1 (2012): 139-150.
- [122] Dragičević, Tomislav, Davor Škrlec, and Marko Delimar. "Modelling different scenarios of virtual power plant operating possibilities." In *MELECON 2010-2010 15th IEEE Mediterranean Electrotechnical Conference*, pp. 452-457. IEEE, 2010.
- [123] Yang, Hongming, Dexin Yi, Junhua Zhao, Fengji Luo, and Zhaoyang Dong. "Distributed optimal dispatch of virtual power plant based on ELM transformation." *Journal of Industrial & Management Optimization* 10, no. 4 (2014): 1297.
- [124] Hawkes, A. D., and M. A. Leach. "Modelling high level system design and unit commitment for a microgrid." *Applied energy* 86, no. 7-8 (2009): 1253-1265.
- [125] Sowa, Torsten, Stefan Krengel, Simon Koopmann, and Johannes Nowak. "Multi-criteria operation strategies of power-to-heat-systems in virtual power plants with a high penetration of renewable energies." *Energy Procedia* 46 (2014): 237-245.

- [126] Malekpour, Ahmad Reza, Taher Niknam, Anil Pahwa, and Abdollah Kavousi Fard. "Multi-objective stochastic distribution feeder reconfiguration in systems with wind power generators and fuel cells using the point estimate method." *IEEE Transactions on Power Systems* 28, no. 2 (2012): 1483-1492.
- [127] Qiao, Songbo, Peng Wang, Tao Tao, and G. B. Shrestha. "Maximizing profit of a wind genco considering geographical diversity of wind farms." *IEEE Transactions on Power Systems* 30, no. 5 (2014): 2207-2215.
- [128] Arabali, Amirsaman, Mahmoud Ghofrani, Mehdi Etezadi-Amoli, M. Sami Fadali, and Yahia Baghzouz. "Genetic-algorithm-based optimization approach for energy management." *IEEE Transactions on Power Delivery* 28, no. 1 (2012): 162-170.
- [129] Mardani, Abbas, Edmundas Kazimieras Zavadskas, Zainab Khalifah, Norhayati Zakuan, Ahmad Jusoh, Khalil Md Nor, and Masoumeh Khoshnoudi. "A review of multi-criteria decision-making applications to solve energy management problems: Two decades from 1995 to 2015." *Renewable and Sustainable Energy Reviews* 71 (2017): 216-256.
- [130] Rabiee, Abdorreza, Mohammad Sadeghi, Jamshid Aghaei, and Alireza Heidari. "Optimal operation of microgrids through simultaneous scheduling of electrical vehicles and responsive loads considering wind and PV units uncertainties." *Renewable and Sustainable Energy Reviews* 57 (2016): 721-739.
- [131] Pei, Wei, Yan Du, Wei Deng, Kun Sheng, Hao Xiao, and Hui Qu. "Optimal bidding strategy and intramarket mechanism of microgrid aggregator in real-time balancing market." *IEEE Transactions on Industrial Informatics* 12, no. 2 (2016): 587-596.
- [132] Liu, Guodong, Yan Xu, and Kevin Tomsovic. "Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization." *IEEE Transactions on Smart Grid* 7, no. 1 (2015): 227-237.
- [133] Yang, Zaiyue, Rui Wu, Jinfeng Yang, Keyu Long, and Pengcheng You. "Economical operation of microgrid with various devices via distributed optimization." *IEEE Transactions on Smart Grid* 7, no. 2 (2015): 857-867.
- [134] Li, Peng, Duo Xu, Zeyuan Zhou, Wei-Jen Lee, and Bo Zhao. "Stochastic optimal operation of microgrid based on chaotic binary particle swarm optimization." *IEEE Transactions on Smart Grid* 7, no. 1 (2015): 66-73.
- [135] Bao, Zhejing, Qin Zhou, Zhihui Yang, Qiang Yang, Lizhong Xu, and Ting Wu. "A multi time-scale and multi energy-type coordinated microgrid scheduling solution—Part I: Model and methodology." *IEEE Transactions on Power Systems* 30, no. 5 (2014): 2257-2266.
- [136] Bao, Zhejing, Qin Zhou, Zhihui Yang, Qiang Yang, Lizhong Xu, and Ting Wu. "A multi time-scale and multi energy-type coordinated microgrid scheduling solution—Part II: Optimization algorithm and case studies." *IEEE transactions on power systems* 30, no. 5 (2014): 2267-2277.
- [137] Farzin, Hossein, Mahmud Fotuhi-Firuzabad, and Moein Moeini-Aghaie. "A stochastic multi-objective framework for optimal scheduling of energy storage systems in microgrids." *IEEE Transactions on Smart Grid* 8, no. 1 (2016): 117-127.
- [138] Ma, Li, Nian Liu, Jianhua Zhang, Wayes Tushar, and Chau Yuen. "Energy management for joint operation of CHP and PV prosumers inside a grid-connected

- microgrid: A game theoretic approach." *IEEE Transactions on Industrial Informatics* 12, no. 5 (2016): 1930-1942.
- [139] Ding, Tao, Shiyu Liu, Wei Yuan, Zhaohong Bie, and Bo Zeng. "A two-stage robust reactive power optimization considering uncertain wind power integration in active distribution networks." *IEEE Transactions on Sustainable Energy* 7, no. 1 (2015): 301-311.
 - [140] Zheng, Weiye, Wenchuan Wu, Boming Zhang, Hongbin Sun, and Yibing Liu. "A fully distributed reactive power optimization and control method for active distribution networks." *IEEE Transactions on Smart Grid* 7, no. 2 (2015): 1021-1033.
 - [141] Mokryani, Geev, Ankur Majumdar, and Bikash C. Pal. "Probabilistic method for the operation of three-phase unbalanced active distribution networks." *IET Renewable Power Generation* 10, no. 7 (2016): 944-954.
 - [142] Lin, Jin, Can Wan, Yonghua Song, Renle Huang, Xiaoshuang Chen, Wanfang Guo, Yi Zong, and You Shi. "Situation awareness of active distribution network: Roadmap, technologies, and bottlenecks." *CSEE Journal of Power and Energy Systems* 2, no. 3 (2016): 35-42.
 - [143] Macedo, Leonardo H., John F. Franco, Marcos J. Rider, and Ruben Romero. "Optimal operation of distribution networks considering energy storage devices." *IEEE Transactions on smart grid* 6, no. 6 (2015): 2825-2836.
 - [144] Abapour, Saeed, Kazem Zare, and Behnam Mohammadi-Ivatloo. "Dynamic planning of distributed generation units in active distribution network." *IET Generation, Transmission & Distribution* 9, no. 12 (2015): 1455-1463.
 - [145] Golshannavaz, Sajjad, Saeed Afsharnia, and Farrokh Aminifar. "Smart distribution grid: Optimal day-ahead scheduling with reconfigurable topology." *IEEE Transactions on Smart Grid* 5, no. 5 (2014): 2402-2411.
 - [146] Nick, Mostafa, Rachid Cherkaoui, and Mario Paolone. "Optimal allocation of dispersed energy storage systems in active distribution networks for energy balance and grid support." *IEEE Transactions on Power Systems* 29, no. 5 (2014): 2300-2310.
 - [147] Xu, Yixing, and Chanan Singh. "Operation strategies of the load aggregator with electric energy storage." In *2012 IEEE International Conference on Power System Technology (POWERCON)*, pp. 1-6. IEEE, 2012.
 - [148] Zhang, Kaiyu, Yiqun Song, Zheng Yan, and Yinghui Yu. "Energy storage capacity optimisation for load aggregators considering the probability of demand response resources' breach." *CIREN-Open Access Proceedings Journal* 2017, no. 1 (2015): 2731-2735.
 - [149] Xu, Yixing, Le Xie, and Chanan Singh. "Optimal scheduling and operation of load aggregator with electric energy storage in power markets." In *North American Power Symposium* 2010, pp. 1-7. IEEE, 2010.
 - [150] Xu, Yixing, Le Xie, and Chanan Singh. "Optimal scheduling and operation of load aggregators with electric energy storage facing price and demand uncertainties." In *2011 North American Power Symposium*, pp. 1-7. IEEE, 2011.

- [151] Chen, Sijie, Qixin Chen, and Yin Xu. "Strategic bidding and compensation mechanism for a load aggregator with direct thermostat control capabilities." *IEEE Transactions on Smart Grid* 9, no. 3 (2016): 2327-2336.
- [152] Hu, Jianqiang, Jinde Cao, Josep M. Guerrero, Taiyou Yong, and Jie Yu. "Improving frequency stability based on distributed control of multiple load aggregators." *IEEE Transactions on Smart Grid* 8, no. 4 (2015): 1553-1567.
- [153] Shafiullah, Md, and Ali T. Al-Awami. "Maximizing the profit of a load aggregator by optimal scheduling of day ahead load with EVs." In *2015 IEEE International Conference on Industrial Technology (ICIT)*, pp. 1342-1347. IEEE, 2015.
- [154] Gao, Ciwei, Qianyu Li, Huixing Li, Haibao Zhai, and Liang Zhang. "Methodology and operation mechanism of demand response resources integration based on load aggregator." *Automation of Electric Power Systems* 37, no. 17 (2013): 78-86.
- [155] Alsharif, Mohammed H., Mohammad K. Younes, and Jeong Kim. "Time series ARIMA model for prediction of daily and monthly average global solar radiation: The case study of Seoul, South Korea." *Symmetry* 11, no. 2 (2019): 240.
- [156] Liu, Lon-Mu, Gregory B. Hudak, George EP Box, Mervin E. Muller, and George C. Tiao. *Forecasting and time series analysis using the SCA statistical system*. Vol. 1, no. 2. DeKalb, IL: Scientific Computing Associates, 1992.
- [157] Tsay, Ruey S., and George C. Tiao. "Consistent estimates of autoregressive parameters and extended sample autocorrelation function for stationary and nonstationary ARMA models." *Journal of the American Statistical Association* 79, no. 385 (1984): 84-96.
- [158] Conejo, Antonio J., Javier Contreras, Rosa Espínola, and Miguel A. Plazas. "Forecasting electricity prices for a day-ahead pool-based electric energy market." *International journal of forecasting* 21, no. 3 (2005): 435-462.
- [159] Contreras, Javier, Rosario Espinola, Francisco J. Nogales, and Antonio J. Conejo. "ARIMA models to predict next-day electricity prices." *IEEE transactions on power systems* 18, no. 3 (2003): 1014-1020.
- [160] Pinson, Pierre. "Estimation of the uncertainty in wind power forecasting." PhD diss., École Nationale Supérieure des Mines de Paris, 2006.
- [161] Wang, Li-Xin. *A course in fuzzy systems and control*. Prentice-Hall, Inc., 1996.
- [162] Lorca, Alvaro, and Xu Andy Sun. "Adaptive robust optimization with dynamic uncertainty sets for multi-period economic dispatch under significant wind." *IEEE Transactions on Power Systems* 30, no. 4 (2014): 1702-1713.
- [163] Heitsch, Holger, and Werner Römisch. "Scenario reduction algorithms in stochastic programming." *Computational optimization and applications* 24, no. 2 (2003): 187-206.
- [164] Sharma, Kailash Chand, Rohit Bhakar, H. P. Tiwari, and Sandeep Chawda. "Scenario based uncertainty modeling of electricity market prices." In *2017 6th International Conference on Computer Applications In Electrical Engineering-Recent Advances (CERA)*, pp. 164-168. IEEE, 2017.
- [165] Powell, W. Richard. "An analytical expression for the average output power of a wind machine." *Solar Energy* 26, no. 1 (1981): 77-80.

- [166] Borowy, Bogdan S., and Ziyad M. Salameh. "Optimum photovoltaic array size for a hybrid wind/PV system." *IEEE Transactions on energy conversion* 9, no. 3 (1994): 482-488.
- [167] Borowy, Bogdan S., and Ziyad M. Salameh. "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system." *IEEE Transactions on energy conversion* 11, no. 2 (1996): 367-375.
- [168] <https://homepages.rpi.edu/~mitchj/handouts/piecewise/>
- [169] Rahimiyan, Morteza, Luis Baringo, and Antonio J. Conejo. "Energy management of a cluster of interconnected price-responsive demands." *IEEE Transactions on Power Systems* 29, no. 2 (2013): 645-655.
- [170] Baringo, Ana, and Luis Baringo. "A stochastic adaptive robust optimization approach for the offering strategy of a virtual power plant." *IEEE Transactions on Power Systems* 32, no. 5 (2016): 3492-3504.
- [171] Baringo, Luis, and Antonio J. Conejo. "Offering strategy via robust optimization." *IEEE Transactions on Power Systems* 26, no. 3 (2010): 1418-1425.
- [172] <https://www.iso-ne.com/isoexpress/web/reports/pricing/-/tree/zone-info>.
- [173] <https://www.umass.edu/windenergy/resourcedata/Paxton>.
- [174] Danish Wind Industry Association, Wind Turbine Power Calculator. [Online]. Available: <http://www.windpower.org/>.
- [175] Zhou, Xiaoping, Leming Zhou, Yandong Chen, Josep M. Guerrero, An Luo, Wenhua Wu, and Ling Yang. "A microgrid cluster structure and its autonomous coordination control strategy." *International Journal of Electrical Power & Energy Systems* 100 (2018): 69-80.
- [176] Saleh, Mahmoud S., Ammar Althaibani, Yusef Esa, Yassine Mhandi, and Ahmed A. Mohamed. "Impact of clustering microgrids on their stability and resilience during blackouts." In *2015 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*, pp. 195-200. IEEE, 2015.
- [177] Han, Renke, Michele Tucci, Andrea Martinelli, Josep M. Guerrero, and Giancarlo Ferrari-Trecate. "Stability analysis of primary plug-and-play and secondary leader-based controllers for DC microgrid clusters." *IEEE Transactions on Power Systems* 34, no. 3 (2018): 1780-1800.
- [178] Ciornei, Irina, Mihaela Albu, Mihai Sănduleac, Enrique Rodriguez-Diaz, Remus Teodorescu, and Josep Guerrero. "Adaptive distributed EMS for small clusters of resilient LVDC microgrids." In *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*, pp. 1-6. IEEE, 2018.
- [179] Nasir, Mashood, Zheming Jin, Hassan A. Khan, Nauman Ahmad Zaffar, Juan C. Vasquez, and Josep M. Guerrero. "A decentralized control architecture applied to DC nanogrid clusters for rural electrification in developing regions." *IEEE Transactions on Power Electronics* 34, no. 2 (2018): 1773-1785.
- [180] Zhao, Zhuoli, Ping Yang, Yuewu Wang, Zhirong Xu, and Josep M. Guerrero. "Dynamic characteristics analysis and stabilization of PV-based multiple microgrid clusters." *IEEE Transactions on Smart Grid* 10, no. 1 (2017): 805-818.

- [181] Al-Awami, Ali T., and Mohamed A. El-Sharkawi. "Coordinated trading of wind and thermal energy." *IEEE Transactions on Sustainable Energy* 2, no. 3 (2011): 277-287.
- [182] Guéret, Christelle, Christian Prins, and Marc Sevaux. "Applications of optimization with Xpress-MP." contract (1999): 00034.
- [183] Mehrjerdi, Hasan. "Modeling and integration of water desalination units in thermal unit commitment considering energy and water storage." *Desalination* 483 (2020): 114411.
- [184] Abrishambaf, Omid, Fernando Lezama, Pedro Faria, and Zita Vale. "Towards transactive energy systems: An analysis on current trends." *Energy Strategy Reviews* 26 (2019): 100418.
- [185] Zia, Muhammad Fahad, Elhoussin Elbouchikhi, Mohamed Benbouzid, and Josep M. Guerrero. "Microgrid transactive energy systems: A perspective on design, technologies, and energy markets." In *IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society*, vol. 1, pp. 5795-5800. IEEE, 2019.
- [186] Yan, Mingyu, Mohammad Shahidehpour, Aleksi Paaso, Liuxi Zhang, Ahmed Alabdulwahab, and Abdullah Abusorrah. "Distribution network-constrained optimization of peer-to-peer transactive energy trading among multi-microgrids." *IEEE transactions on smart grid* 12, no. 2 (2020): 1033-1047.
- [187] Wu, Yiwei, Jian Shi, Gino J. Lim, Lei Fan, and Anahita Molavi. "Optimal management of transactive distribution electricity markets with co-optimized bidirectional energy and ancillary service exchanges." *IEEE Transactions on Smart Grid* 11, no. 6 (2020): 4650-4661.
- [188] Wang, Yifei, Zhiheng Huang, Zhenhao Li, Xi Wu, Loi Lei Lai, and Fangyuan Xu. "Transactive energy trading in reconfigurable multi-carrier energy systems." *Journal of Modern Power Systems and Clean Energy* 8, no. 1 (2019): 67-76.
- [189] Zia, Muhammad F., Mohamed Benbouzid, Elhoussin Elbouchikhi, S. M. Mueeen, Kuaanan Techato, and Josep M. Guerrero. "Microgrid transactive energy: Review, architectures, distributed ledger technologies, and market analysis." *Ieee Access* 8 (2020): 19410-19432.
- [190] Li, Jiayong, Chaorui Zhang, Zhao Xu, Jianhui Wang, Jian Zhao, and Ying-Jun Angela Zhang. "Distributed transactive energy trading framework in distribution networks." *IEEE Transactions on Power Systems* 33, no. 6 (2018): 7215-7227.
- [191] Nizami, M. S. H., M. J. Hossain, BM Ruhul Amin, Muhammad Kashif, Edstan Fernandez, and Khizir Mahmud. "Transactive energy trading of residential prosumers using battery energy storage systems." In *2019 IEEE Milan PowerTech*, pp. 1-6. IEEE, 2019.
- [192] Hu, Junjie, Guangya Yang, Koen Kok, Yusheng Xue, and Henrik W. Bindner. "Transactive control: a framework for operating power systems characterized by high penetration of distributed energy resources." *Journal of Modern Power Systems and Clean Energy* 5, no. 3 (2017): 451-464.
- [193] Cheng, Jianqiang, Richard Li-Yang Chen, Habib N. Najm, Ali Pinar, Cosmin Safta, and Jean-Paul Watson. "Chance-constrained economic dispatch with renewable energy and storage." *Computational Optimization and Applications* 70, no. 2 (2018): 479-502.

- [194] Riaz, Muhammad, Sadiq Ahmad, Irshad Hussain, Muhammad Naeem, and Lucian Mihet-Popa. "Probabilistic Optimization Techniques in Smart Power System." *Energies* 15, no. 3 (2022): 825.
- [195] Shapiro, Alexander, Darinka Dentcheva, and Andrzej Ruszczyński. *Lectures on stochastic programming: modeling and theory*. Society for Industrial and Applied Mathematics, 2021.
- [196] Van Ackooij, Wim, Riadh Zorgati, René Henrion, and Andris Möller. "Chance constrained programming and its applications to energy management." *Stochastic Optimization-Seeing the Optimal for the Uncertain* (2011): 291-320.
- [197] Van Ackooij, Wim. "Chance constrained programming: with applications in Energy Management." PhD diss., Ecole Centrale Paris, 2013.
- [198] Kazemzadeh, Narges, Sarah M. Ryan, and Mahdi Hamzeei. "Robust optimization vs. stochastic programming incorporating risk measures for unit commitment with uncertain variable renewable generation." *Energy Systems* 10, no. 3 (2019): 517-541.
- [199] Kerstine Appunn, Yannick Haas, Julian Wettengel. "Germany's energy consumption and power mix in charts." www.cleanenergywire.org.

Vitae

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Education

Electrical Engineering PhD part time enrolment King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia
Electrical Engineering M.Sc. Jan. 2016 – GPA (3.917 out of 4.0) King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia
Electrical Engineering B.Sc. May 2013 – GPA (3.942 out of 4.0) King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia

Master and Bachelor Degrees

-My master's thesis is about "Hybrid Distributed Generation System (HDGS) Modelling for Smart Self-Healing Electric Microgrids".
-My bachelor degree was in the power field and my senior project design was about "Solar Tracking and Battery Charging System"; where the sun is tracked on a two axes system (360 degrees).

Additional Courses

Computer Science College, Al-Fayoum University
Al-Fayoum, Egypt

**Object-Oriented Programming in C++ 2009, Fundamental Physics 2009, Calculus 2009, Computational Linguistics 2009,
English Language 2009**

Experience and Skills

Mar. '18 to Present CEO, TIEPCO, Dammam, Saudi Arabia

- My responsibilities include increasing the performance of the company, fixing the existing weaknesses, and finding potential opportunities.

Feb. '17 to Present Part Time PhD Student, KFUPM, Dhahran, Saudi Arabia

- Finished nine credits and taking six currently out of 42 (including the dissertation).

Jul. '16 to Mar. '18 R&D Sr. Eng., TIEPCO, Dammam, Saudi Arabia

- My responsibilities include increasing the performance of the company, fixing the existing weaknesses, and finding potential opportunities and eventually creating and managing renewable energy segment.

Feb. '15 to present Papers Published

- Abdellatif, Hussein, Mujahid N. Syed, Md Ismail Hossain, and Mohammad A. Abido. "Standalone Hybrid Renewable Energy System Optimization Using Linear Programming." *Arabian Journal for Science and Engineering* (2022): 1-16.
- Abdellatif, Hussein, Md Ismail Hossain, and Mohammad A. Abido. "Parameters Estimation of PV Models Using Artificial Neural Network." *Arabian Journal for Science and Engineering* (2022): 1-10.
- Abdellatif, Hussein, and Adel Alshibani. "Major factors causing delay in the delivery of manufacturing and building projects in Saudi Arabia." *Buildings* 9, no. 4 (2019): 93.
- Abdellatif, Hussein, Mohammad Al-Muhaini, and Muhammad Khalid. "Hybrid Distributed Generation System Modeling for Smart Self-Healing Electric Microgrid." In *2018 IEEE Industry Applications Society Annual Meeting (IAS)*, pp. 1-8. IEEE, 2018.
- Adel, Hussien, Ahmed S. Alahmed, and Ibrahim Elamin. "Possible privatization schemes for power generation sector in Saudi Arabia." In *2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE)*, pp. 171-175. IEEE, 2018.
- Abdellatif, Hussein, Mohammad AlMuhaini, and Muhammad Khalid. "Reliability Analysis of an Integrated PV System Using Markovian Modeling." In *2018 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 544-548. IEEE, 2018.
- Abdellatif, Hussein, and Ibrahim El-Amin. "Markov modeling of solar radiation and storage sizing." In *2015 IEEE 8th GCC Conference & Exhibition*, pp. 1-6. IEEE, 2015.

Jan. '21 to present Online Courses

- I have taken "Live Action Video Creation" online course with Animaker Inc.
Authenticity of this certificate can be verified through:
Credential ID 2282981

Mar. '12 to present edx Online Courses

- I have taken Electronics online course with MIT, Course 6.002x. I got a grade of A, the highest grade.

Authenticity of this certificate can be verified at:

<https://verify.edxonline.org/cert/7b441f0315f84dff8b6b7300a1f6d113>

- I have taken Solar Energy online course with Delft University, ET3034Tux course. I got 100%.

Authenticity of this certificate can be verified at:

<https://verify.edx.org/cert/da207215fcf44fe9949a3973495195f4>

- I have taken “embedded systems” online course with Austin University, UT.6.01x course.

Authenticity of this certificate can be verified at:

<https://verify.edx.org/cert/098fcc0d3b96489280ba1d6c91231153>

- I have taken “Solar Energy: Photovoltaic (PV) Energy Conversion” online course with Delft University, PV1x course.

Authenticity of this certificate can be verified at:

<https://courses.edx.org/certificates/e97056fb250c47e1a53432af30eb428d>

Jan. '09 to Present Electrical/Non-Electrical Software

- Worked on some programs related to EE such as: PSPICE, Logic Works, MATLAB, Multisim, Turbo Debugger, ETAP, Power World, Cassy Lab, Microsoft office, JCreator, Xilinx, and Keil Uvision, GAMS, and SAP Business One.

Jan. '14 to May '16 Private Tutoring

- Giving private lessons to students at KFUPM.

Jul. '15 to Jan '16 IEEEEXTREME 9.0

- I became an IEEEEXTREME 9.0 ambassador for region 8 (IEEE) for year 2015.

Jan. '15 to Jan '16 Professional Committees

- I was an IEEE member and the chair of the graduate committee of the IEEE-KFUPM student branch (2015).

- Worked with the electrical engineering club at KFUPM.

Jan. '14 to Jan '16 Research Assistant

- Studied masters and taught laboratories at KFUPM.

- I taught electrical machines lab (senior level), electric energy engineering lab (junior level), electromechanical devices lab two times (junior level). I am currently teaching fundamentals of electrical circuits lab (sophomore level).

Jan. '14 to Jan '16 Advanced Courses

- I have taken courses about HVDC, power system protection, power system reliability, power system planning, and intelligence control.

Jan. '14 to Jan. '15 Volunteering Activities

- Help sessions organizer and a volunteer teacher at KFUPM.

- Worked with the EE club at KFUPM.

Sep. '09 to '13

Grader, Physics and Math Departments

KFUPM, Dhahran, Saudi Arabia

- Grader Math 001/ Math 002 (twice) / Phys. 101/ Phys. 102 (4 times). (8 times = 6 semesters + 2 summer).
- For Math, I graded two homework assignments a week for four sections each with around 30 students.
- For physics, I graded one quiz a week for six sections each with about 30 students.

Dec. '11 to Dec. '13

Educational videos Translator

- Part time job as a tutorial videos' translator at Remal IT.

Mar. '13 to May '13

Educational Game

- Worked as a part time job to make the educational content of a game that was built by programmers at Remal IT.

Jan. '09 to May '13

Personal and University Projects

- Worked on many projects, and some of them are: FM transmitter, Power project on ETAP, voice transmission over laser.
- Worked on a sun tracking solar system based on two axes, which was my senior project.

Feb. '13

IELTS

- Listening 8, Reading 7, Writing 7, Speaking 7, and overall band score is 7.5

Jun. '12 to Aug. '12

Summer Trainee, Schlumberger, Khobar, Saudi Arabia

- I spent a two months summer training at Schlumberger; In the D&M segment.

Open to open

General Skills

- I have obtained some skills from my experience such as electrician, PC assembler, PC programmer, bilingual, grader, teacher, presenter, report writer and coordinator, and manager.

Other Skills

Working in a group, working individually, and group leading.

Achievements

Awarded First Level Honor in school. Awarded First Level Honor in bachelor with a GPA of 3.942 out of 4.00. Awarded First Level Honor in masters with a GPA of 3.9 out of 4.00