THE IMPACT OF WIND SPEED MODELING ON THE RELIABILITY OF MICROGRIDS

BY

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Dedicated to

My beloved father and mother, for their prayers, love, support, and encouragement, which brought to me all the success and progress in my life.
I am always grateful to my dear wife for her love, interest and supporting me.
My great appreciation to my brothers, sisters, and all my family for their kind care and happiness for my success.

God bless you and reward you all the best

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All praise and thanks to Almighty Allah for His countless blessings

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LIST OF ABBREVIATIONS

DG	:	Distributed Generation
EENS	:	Expected Energy Not Supplied
SAIDI	:	System Average Interruption Duration Index
CAIDI	:	Customer Average Interruption Duration Index
SAIFI	:	System Average Interruption Frequency Index
ASAI	:	Average Service Availability Index
ARMA	:	Auto- Regressive Moving Average
WTG	:	Wind Turbine Generator
RBTS	:	Roy Billinton Test System
EMCS	:	Encoded Markov Cut Set
PACF	:	Partial Autocorrelation Function
ACF	:	Autocorrelation Function
AIC	:	Akaike Information Critera
MC	:	Markov Chain
CDF	:	Cumulative Distribution Function
RMSE	:	Root Mean Square Error

MAD	:	Mean Absolute Deviation
MTTF	:	Mean Time To Fail
MTTR	:	Mean Time To Repair
MTBF	:	Mean Time Between Failures
A	:	Availability
U	:	Unavailability
AIF	:	Average Interruption Frequency
AID	:	Average Interruption Duration
FD	:	Failure Duration
ENS	:	Energy Not Supplied
CPT	:	Capacity Probability Table
DPT	:	Demand Probability Table
LOLP	:	Loss Of Load Probability

ABSTRACT

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Wind power is the most popular renewable resource worldwide due to its efficiency and cost. Nevertheless, the complexities of integrating conventional and renewable resources into the active networked distribution system can be prohibitive. Effective planning of wind power integration requires accurate wind speed modeling, and achieving this accuracy is challenging. One of the main challenging issues in integrating wind power sources is how to forecast the long-term wind speed and study its impact on the reliability of the microgrids.

The objective of this thesis is to examine different approaches to model the wind speed and power output of the Wind Turbine Generator (WTG). Then, the WTG model will be integrated into a Markov model to assess the impact of wind speed modeling on the reliability of microgrids. In the first phase of this research, Auto-Regressive Moving Average (ARMA) time series, the Markov chains, and probability distribution functions will be used to model and forecast the stochastic behavior of wind speed. Then, the WTG's power output will be simulated using the speed-power characteristics of a WTG model. The performance and effectiveness of the different wind speed models will be analyzed using different statistical tests.

The second phase will demonstrate the effect of wind speed modeling on the reliability analysis of the microgrids. The load demand for different residential, commercial, and industrial customers will be modeled. Also, Markov modeling will be used to evaluate the reliability indices for the microgrid. Then, the WTG will be integrated into this model to reflect their impact on the reliability indices. At the end, different measures will be used to assess the impact of the wind-speed models on the local and system reliability indices, mainly System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI).

ملخص الرسالة

الاسم الكامل : أسعد فرج رايق بزره

عنوان الرسالة : تأثير النماذج المختلفة لسرعة الرياح على دراسة موثوقية شبكات التوزيع النشطة

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طاقة الرياح هي أكثر أنواع مصادر الطاقة المتجددة شعبية في جميع أنحاء العالم المتجددة نظرا لكفاءتها وتكلفتها. ومع ذلك، فان تعقيدات دمج الموارد التقليدية والمتجددة في نظام التوزيع الشبكي نشط يمكن أن تكون مرتفعه. التخطيط الفعال لدمج طاقة الرياح يتطلب دقة في تمثيل سرعة الرياح وتحقيق هذه الدقة يمثل تحديا. واحدة من القضايا الصعبة الرئيسية في دمج مصادر طاقة الرياح هي طريقة تنبؤ سرعة الرياح على المدى الطويل ودراسة تأثيرها على موثوقية الشبكات الذكية.

هدف المشروع الرئيسي هو اختبار طرق متعددة لتمثيل سرعة الرياح والطاقة المنتجة لمولد توربين الرياح. بعد ذلك سيتم دمج نموذج مولد توربين الرياح مع نموذج ماركوف لتقييم موثوقية شبكات التوزيع النشطة. في المرحلة الأولى من هذا المشروع سيتم تمثيل سرعة الرياح العشوائية عن طريق استخدام دوال الكثافة الاحتمالية واستخدام السلسلة الزمنية للانحدار الذاتي والمتوسط المتحرك واستخدام سلسلة ماركوف. بعد ذلك سيتم إنتاج الطاقة من مولد توربين الرياح باستخدام خصائص مولدات مختلفة. أداء وفعالية مختلف نماذج سرعة الرياح سيتم دراستها بعد ذلك باستخدام طرق تحليل مختلفة.

في المرحلة الثانية من هذا المشروع سيتم شرح تأثير النماذج المختلفة لسرعة الرياح على دراسة موثوقية شبكات التوزيع النشطة. سيتم تمثيل بعض نماذج الأحمال لعملاء السكن والتجارة والصناعة المختلفين ونموذج ماركوف سيستخدم لتقييم مؤشرات موثوقية شبكة توزيع الطاقة. بعد ذلك سيتم دمج مولدات توربين الرياح والمولدات التقليدية في هذا النموذج لدراسة تأثيرهم على مؤشرات الموثوقية. في الأخير سيتم اقتراح مؤشرات مختلفة لتقييم تأثير النماذج المختلفة لسرعة الرياح على مؤشرات الموثوقية المحلية ومؤشرات موثوقية النظام مثل مؤشر معدل تردد الانقطاع للنظام ومؤشر معدل مدة الانقطاع للنظام.

CHAPTER 1

INTRODUCTION

1.1 Overview

The demand for electrical power is growing day after day, due to this increasing demand, it is necessary that power systems provide satisfactory electrical energy with good and adequate reliability and quality.

Reliability in general is the probability that a system would achieve its mission adequately. From a power system point of view, power reliability can be defined as an uninterrupted power supply, and it relates to the absence of equipment outages and customer interruptions. Several factors may cause outages and interruptions such as equipment failures, faults, environmental causes, and human errors.

A power system is composed of a generation system, transmission system, and distribution system. The generation system produces power regarding customers' demand. The transmission system transports bulk power over long distances from the generation system to the distribution system. The distribution system delivers electricity to the end users, residential, commercial, industrial, etc. [1].

In the past, electric utilities were paying the most attention to the generation and transmission systems more than the distribution system in reliability modeling and

evaluation. That is because they are capital intensive, and their inadequacy can have severe economic consequences. Reliability assessment for a generation system can be carried out by using one day in 10 years loss of load expectation criterion. Transmission system reliability is evaluated using sophisticated computer models [2].

Recently, the interest has shifted toward distribution systems. Statistics and analysis of customers' failures of most utilities indicate that the distribution system is the most effective element of reliability because of the radial nature of most distribution systems, the large number of components, and the sparsity of protection devices and switches. In addition to that, the components of a distribution system are cheap, and its effects are local compared to the magnificent effects of generation and transmission systems on the whole power system. Therefore, improving distribution reliability is the key to improving customer reliability.

1.2 Thesis Motivation

The enormous growth of customers and power demand in recent years results in considerable issues for power quality and reliability. These issues were caused due to the large number of non-linear loads used by costumers in addition to interruptions and outages of electricity.

Distributed generations (DG) and Microgrids can improve the power quality and reliability. The impacts of DGs and Microgrids can be summarized as:

- DGs help to maintain and improve the voltage profile at distribution system.
- DGs contribute to increase the power capacity of the main electric utility during peak time.

- Microgrid through the sophisticated power electronic interfaces can provide high-quality power in term of voltage and frequency.
- During failures of main electrical supply or faults at any section, DGs as backup generators would take over and provide power to the system after isolating the faulted section.
- The intelligent control system of the Microgrid helps with transition of the DGs from grid-connected to stand-alone mode during failure or outage of the utility grid.

Power utilities are interested in utilizing renewable energy resources for several environmental and economic reasons. Modeling and integrating conventional and renewable resources into the active networked distribution system increase the complexity in modeling and analyzing the reliability of the system.

Wind energy is one of the most attractive renewable resources nowadays due to several factors, some of these factors include: efficiency, competitive cost and less pollution. On the other hand, the wind speed is highly stochastic. Integrating the wind power in the grid needs an accurate modeling and forecasting of the wind speed.

The objective of any power system is to deliver power to the customer's load in an efficient and reliable way. One significant factor in the design of any power system is measuring and evaluating the reliability of the system. The reliability of any power system can be measured by its probability to supply the load at any time and under the normal conditions. Evaluating distribution system reliability is important for improving the operational and maintenance of the system.

Different factors should be considered when evaluating the reliability impact of the DG on the local load, such as fuel availability, power output, the unit's failure rate, repair time, and starting time. Therefore, new research and studies are needed to improve the system's reliability assessment techniques.

Reliability is a very important issue for power systems design and operation, and it has significant impact on safety and economy. Emergency communications, certain transportations, and so many other essential services need reliable electricity. A severe blackout occurred on September 28, 2003, in Italy and Swaziland. It lasted for more than two days. Around 56 million people were affected by this blackout. The Italian electrical system collapsed. The mobile communication system started to fall. Many airline flights were cancelled. Thirty thousand people were stuck on trains. Other hundreds were trapped in underground train stations. And three people died in that event [3].

Besides the safety hazard, outages and interruptions cause huge effects on the economy of power utilities and customers. Power outages cost the utility millions of dollars in service cut-off, re-operation, equipment repairs and maintenance. The Electric Power Research Institute (EPRI) and the U.S. Department of Energy (DOE) have conducted research about the cost of electricity outages, which is estimated at 30 to 400 billion dollars per year [4]. Due to the importance of reliability, this research will study the impact of wind speed modeling on the reliability of microgrids.

1.3 Thesis Objectives

The objective of this research is to examine and develop engineering methods to evaluate the impact of wind speed modeling on the reliability of Microgrids. The main objectives of this research are:

1- To model and forecast the stochastic nature of wind speed using Auto-Regressive Moving Average (ARMA), Markov chain models, and probability distribution functions. Then, the WTG's power output will be simulated using the speed-power characteristics of WTG model.

2- To compare between the different wind speed models using several goodness of fit tests, such as, root mean square error (RMSE) and mean absolute deviation (MAD).

3- To evaluate the reliability of a Microgrid including the WTG. The Roy Billinton Test System (RBTS) will be used in this thesis for WTG integration and analysis. Several system and load reliability indices will be computed and compared such as, SAIFI, SAIDI, and ENS.

1.4 Thesis Organization

The core of this research is to study the impact of wind speed modeling on the reliability of microgrids. In order to build a general view on the importance of modeling and reliability analysis, chapter 1 demonstrates the thesis motivation, and the main objectives for this research. Chapter 2 gives literature review on the electric microgrids, explains the importance of modeling wind speed, and what is the advantages of improving the

reliability in the active network. Chapter 3 starts the first phase of this research, which is modeling and forecasting wind speed and power, and determining the best modeling method using goodness of fit tests. Chapter 4 explains the basics of the reliability calculations, and how to use Markov model in the reliability analysis. Chapter 5 achieves the objective for the second phase of this research, where the impact of the wind speed modeling on the reliability is found by integrating different types of DGs in the RBTS network. Chapter 6 shows the general conclusions for this research and the future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Electric Microgrids

Renewable distributed generation (DG) is an alternative generation system that provides electricity to the distribution area using renewable energy sources such as wind power, solar photovoltaic cells, etc. The need for renewable DG comes from several reasons that can be summarized as:

- Contribution in supplying power and improving power quality and reliability.
- Gradual depletion of fossil fuel resources that leads to the need for other natural resources.
- Reduction of environmental pollution and global warming that caused by exhausts from combustion of fossil fuels.

Conventional distribution network is a passive distribution system that received power only from the utility's grid, which means power is transmitted in one direction. However, when the distribution network is integrated with DGs, it becomes an Active distribution system with a bidirectional power flow.

In order to improve the performance of the active distribution network, some management technologies may be implemented. In that case, active distribution network becomes a Microgrid or smart grid network. Microgrid is an active distribution network

with a power electronic interface and control system that provides electricity to local area or customers. The control system makes Microgrid compatibles with the main grid and meets its requirements and regulations for the power security and reliability. This makes Microgrid is considered as a single controlled unit to the main power utility. DGs or microsources (MSs) in Microgrids are smaller in capacity than the large generators in conventional power plants. IEEE recommends that the maximum capacity of Microgrid generation is restricted to 10 MVA. Therefore, to supply more power, several Microgrids can be interconnected to a common distribution network [5]. Microgrids have two operation modes, grid-connected and stand-alone. In grid-connected mode, the Microgrid is connected to the main grid and exchanges power with the main grid. In case of any interruption or outage in the main grid, the Microgrid switches over to stand-alone mode by isolated the system from the main grid and supplying power to the priority loads.

2.2 Modeling and Forecasting Wind Speed and Power

Due to the increasing cost of fossil fuel and the pollution from the conventional energy sources, renewable resources are becoming an important factor in the power system. The demand for wind power increased in the last few years, which has made the cost decrease significantly. In Europe, nearly 10% of the installed power was from wind power in 2011, and the goal is to reach 20% of the total power supply from renewable sources in 2020 [6].

The positive effect of adding wind to power systems is the reduction of emissions that come from electricity production as well as the cost of long-term operations. This is because the wind is free source, while fuel, natural gases, and oil are not [7].

Due to the increase in wind power penetration, more accurate wind forecasting models are needed, either for long-term or short-term [8].

There are various forecasting models; some of the models perform very well with short-term prediction, while others perform better in long-term prediction. Recently, with the development of artificial intelligence and mathematical techniques, a lot of new methods were put forward [9].

Modeling wind speed for both short- and long-term forecasting is challenging. Several probability distribution functions have been suggested in the literature [10-16]. The Weibull and its special case, Rayleigh, have been widely recognized in the literature [11].

Reference [13] presents an excellent statistical study of modeling wind speed using Weibull distribution. In [13], the two-parameter Weibull distribution was used, and three methods were applied to estimate the parameters, namely the maximum likelihood, minimum chi square, and least square method. The results showed that the maximum likelihood was the best estimator among the three proposed methods. Markov chain Monte Carlo (MCMC) technique was also used in [12] to estimate the parameters of the Weibull distribution.

In [14], seasonal wind speed variations are considered when modeling wind speed using the Weibull distribution. The maximum likely estimation (MLE) and the method of moments (MOM) were used in [14] to determine the parameters of the Weibull distribution.

In [17], three goodness-of-fit tests were used to investigate several distributions, such as Beta, Exponential, Gamma, Logistic, Lognormal, Uniform and Weibull. The goodness-

of-fit tests used in [17] were chi-square, Kolomogrov-Smirnov, and Anderson-Darling tests. From the comparison, Weibull distribution was found to be the best at representing wind speed data.

Time series models have also been used in the literature [18-20] to model the chronological nature of wind speed. The Auto-Regressive Moving Average (ARMA) model was used in [18, 19] while the Auto-Regressive Integrated Moving Average (ARIMA) model was used in [21, 22].

The autoregressive moving average ARMA model is one of the most popular time series models in forecasting the wind speed. ARMA, exponential smoothing and seasonal index were used for predicting incidence of Newcastle disease, and evaluating the precision of these three models [23]. The results showed that the ARMA model was the best model to predict the disease, and have the fittest predicting effect.

The autoregressive moving average model (ARMA) is one of the most attractive methods in forecasting. In addition, there are other methods like the pdf curve and Markov model for making predictions, and due to the increase in wind power penetration, more accurate wind forecasting models are needed, either for long-term or short-term [24].

Using ARMA model, the trend for forecasted wind speed in the time series is similar to that of the actual velocities, so the use of mean and standard deviation of original values for the standardization is accurate [25].

Furthermore, the Markov chain is one of the best models for representing the dynamic behavior of the system, but constructing the transition matrix for a large number of components or states is complicated. Several references in the literature used either the

first or second order Markov chain to model wind speed, such as in [13, 26-27]. Reference [27] investigated the effect of the Markov chain state space size on the accuracy of wind speed modeling. It was found in [28] that the Markov chain is of limited use, as the synthetic data generator for micro grid models and other applications requires short simulation time steps.

To simulate the power output of the WTG, the relationship between wind speed and WTG's power output will be utilized. The power output for each unit can be calculated based on wind speed and the parameters like rated wind speed, cut-in wind speed, cut-out wind speed, and rated power output of the wind turbine [29, 30, 31-33].

2.3 Reliability Analysis of Electric Microgrids

Distribution system is the final stage in the power system and it is connected directly to the customers. In order to provide electricity to those customers with an acceptable level of reliability, the reliability of the distribution system must be investigated and evaluated to decide whether it needs any improvement or not. Therefore, huge efforts have been done in the area of assessing and evaluating the distribution system reliability.

Distribution system reliability depends on customer load points and on the limited local distribution system, unlike generation (G) and transmission (T) systems, which are based on the complete power system. Because of that, reliability evaluation of the distribution system is not as difficult as the G&T systems.

Since the wind is a stochastic source, integrating the wind energy sources and evaluating their impact on the reliability of the system is a challenging task. The cost and the

reliability of the system have had significant changes due to the variability and the nature of wind power [7].

It is difficult to accurately assess wind power output for long time ranges. This is because the accuracy of forecasted wind speed decreases with lead time. If the wind power installed in the power system is increased, the impacts of wind power become significant. Reference [7] states that the addition of wind generation has a positive effect on increasing the reliability of the power system, and this increase is related to the wind power penetration in the system.

To have accurate assessment of power system reliability, forecasting can be used to reduce the error and the cost of planning and operating the system. Forecasting can be made long or short term, and using different forecasting models will benefit the generation dispatch in the electricity market and system security in different aspects. The long-term forecasting can provide useful planning to organize the schedule of the connection of wind turbines and conventional generators [11]. One known limitation of any statistical prediction model is that the extreme events can't be predicted.

Several studies in the literature evaluated the impact of WTG on the reliability assessment of power systems. In [34], an ARMA time series model was proposed for a single wind farm. Reference [35] extended the work presented in [34] by examining the system when the conventional generations are replaced by Wind Energy Conversion Systems (WECS). References [36-38] extended the concept of utilizing multiple wind farms presented in [25] by considering different level of correlation among different wind farms.

The research about reliability is concentrating on how to model the power system with different configurations and operations and how to calculate reliability interruptions and indices. These interruptions could be momentary interruptions or sustained interruptions [39]. Momentary interruption is defined as single operations of interruption results in zero voltage for less than 5 minutes. Sustained interruption is an interruption within a period of 5 minutes or longer [40]. Beside to the interruptions, Reliability indices must be computed to evaluate the reliability. Reliability indices represent average values of the reliability characteristic for the system. There are two types of indices, load point indices and system indices [41]. Load point indices include failure rate (λ), outage time (r), annual unavailability (U), and expected energy not supplied ($EENS$). System indices provide additional representation for the system behavior and reliability [42].

Reliability evaluation is categorized into two main techniques, analytical and simulation [43]. In the analytical technique, the system is represented by a mathematical model and reliability is evaluated by a mathematical equations applied to this model. However, simulation method, such as Monte Carlo simulation, assesses the reliability by simulating the actual system and its random behavior [44]. Analytical technique is the most common because it is efficient and provides the needed results whereas simulation technique requires a large amount of computing time.

A direct method for reliability evaluation in transmission and distribution system was proposed in [45]. Three indices have been widely used to assess the reliability, frequency of failure, average duration of outage, and average total hours of outage in a year. The technique employed in [45] was the minimal cut set. After determining all minimal cut sets, the system was represented in a series-parallel configuration. Then, reliability

indices were calculated easily by the series and parallel equations. This approach uses simple and general equations that do not involve complex conditions in practical systems. On the other hand, it considers only the failure rates without including successful states, which saves effort and time.

An educational test system (RBTS) has been developed with overall power system reliability assessment in [46]. Main reliability indices in [46] were the failure rate, the average duration of failure, and the annual unavailability, which we called earlier the load point indices. System indices were also calculated for each bus in the system. Overall system evaluation incorporated the three functional zones of generation, transmission and distribution in the analysis. By using the approach in the literature, load point indices and system indices for the RBTS were obtained. The results of the evaluation showed that failures at distribution affect the overall system reliability. The RBTS system has been widely used in reliability studies ever since.

Reference [47] suggested a new method to analyze and assess the current reliability of an operating power system with an equivalent model based on the Markov chain. The Markov chain is a method used to evaluate reliability based on the probability of system states. The power system here is divided into three states, normal state, fault state, and risk state. The RBTS-Bus 6 system was used to test this approach. The calculation is done by the Monte Carlo simulation program. Calculations and results indicate that the proposed algorithm is efficient and practical.

CHAPTER 3

WIND SPEED MODELING AND FORECASTING

3.1 Modeling and Forecasting Wind Speed

To start the modeling and forecasting process for the wind speed, historical hourly wind speed data must be collected. In this research, wind speed for Al Dhahran area- KSA for the year of 1998 is used. The collected wind speed has minimum speed is 2.2 m/sec, maximum speed is 9.3 m/sec, and the mean speed is 3.6203.

Starting with one year of wind speed data for Dhahran city 1998, the outliers are removed where the outliers are defined as the data points that diverge from the data population. In this research, the outlier is considered to be any point that is more than three standard deviations away from the mean.

Depending on the wind speed data after removing the outliers, Auto-Regressive and Moving Average (ARMA) time series, the Markov chains, and probability distribution functions will be used in order to model and forecast this wind speed data. The historical hourly wind speed for Al Dhahran after removing the outliers is shown in Fig. 3.1 below,

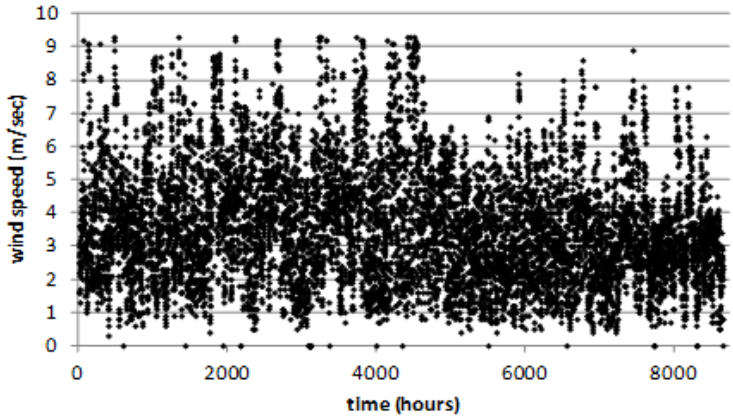


Figure 3.1: Historical Wind Speed for AL Dhahran 1998

3.1.1 Auto-Regressive Moving Average Model (ARMA)

The Autoregressive Moving Average (ARMA) time series model will be used to model and forecast the wind speed. In this method, the correlation and the average are used, where the auto-regressive (AR) is defined as the lags that show the difference between the values in the series that appear in the forecasting equation. The moving average (MA) is defined as the lags for the forecasting errors.

The autoregressive reflects the coefficients that have an infinite correlation. It has a long memory due to the relation between the present value and all previous values. AR cannot be used to reflect a short memory series because the present value in the series has a correlation with all previous values.

To reflect short memory, MA is the best approach where the function can be built from finite past values. AR and MA are emerged into one time series, ARMA, which gives a stationary stochastic method to reflect any time series.

To measure the relation between present values and past ones in the series, the partial autocorrelation and autocorrelation methods are used to give values from the past data that can be useful to use in forecasting future values; and by these two methods, the order for ARMA is defined.

The partial autocorrelation function (PACF) defines the correlation between the intervals and considers the values between these intervals. The autocorrelation function (ACF) defines the correlation in the intervals, regardless of the values between these intervals.

So to identify the order for ARMA, speed data must be proved to be stationary, where "stationary" means that the data does not follow any trend, also when the time is shifted, the stochastic style does not change, and by using the Dickey-Fuller test; wind speed data in this research is proved to be stationary.

The next step is to select the appropriate ARMA model, which means finding the best values of p and q for ARMA (p, q) style. To find the best order for (p, q), PACF and ACF must be examined based on the following rules:

- If the PACF for the series presents a sharp cutoff and/or the autocorrelation at lag-1 is positive, then the AR term in the model must be increased. The AR's number is indicated by the lag at which the PACF cuts off.

- If the ACF for the series presents a sharp cutoff and/or the autocorrelation at lag-1 is negative, then the MA term in the model must be increased. The MA's number is indicated by the lag at which the ACF cuts off.

The main objective is to model the wind speed for Dhahran city in the eastern province of Saudi Arabia, and find the forecasted wind speed using the ARMA model. This can be represented in Fig. 3.2 below:

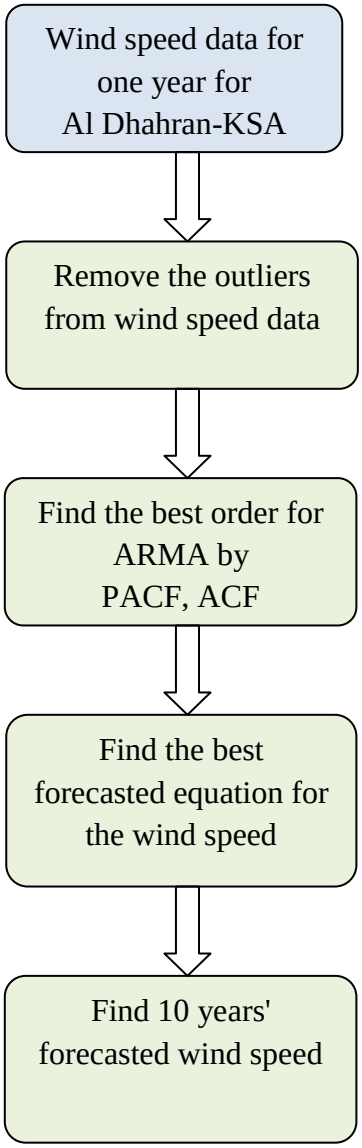


Figure 3.2: Flow Chart for the Methodology Stages in ARMA Model

The main steps for the modeling and evaluating process are as follows:

1. Historical wind speed data is collected for Dhahran area - Saudi Arabia.

2. Remove the outliers from wind speed data.

3. The best order for ARMA model is found using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

4. ARMA model is used to find the best equation for forecasting wind speed.

5. Forecasted wind speed for any period of time.

Starting with one year of wind speed data for Dhahran city 1998, the outliers are removed where the outlier is considered to be any point that is more than three standard deviations away from the mean as shown in Fig. 3.1.

To identify the order for ARMA, the autocorrelation and partial autocorrelation diagrams must be examined for the stationary time series as shown Figure 3.3, and 3.4.

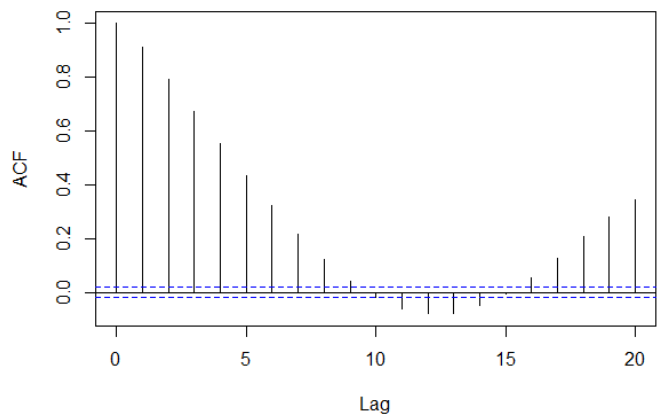


Fig. 3.3: ACF for the Historical Wind Speed Data

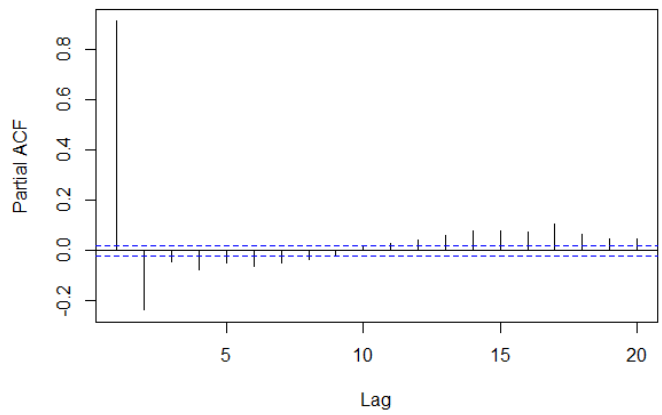


Fig. 3.4: PACF for the Historical Wind Speed Data

By checking the ACF and PACF in Fig. 3.3 and 3.4, the following observations are noted:

- The correlation at lag 1 is significant and positive, and
- The PACF shows a sharper "cutoff" than the ACF

Thus, according to the rules above, the series displays an AR (3) signature. Therefore, the order of the AR term will be set to 3, i.e., ARMA (3, 0) model. But after applying this model, some significant spikes in PACF and ACF are still shown; so, the order of MA will be increased until the elimination of all significant spikes, in which the order (3, 3) will achieve this objective.

To support this selection of ARMA, the ARMA model can be tested for more than one model of p and q and compare which model has the best Akaike Information Critera (AIC) value. The AIC is a widely used measure of a statistical model. It basically quantifies the goodness of fit and the simplicity/parsimony of the model into a single statistic [23].

When comparing two models, the one with the lowest AIC value is generally "better". Table 3.1 shows different AIC for different combinations of p and q.

Table 3.1: Different AIC Values for Different ARMA Orders

		p			
		0	**1**	**2**	**3**
q	**0**	34352.6	18831.4	18324.25	18309.95
	1	26262.6	18229.7	18267.7	18229.7
	2	22491.2	18346.6	18221.6	18213.7
	3	20589.32	18309.83	18207.08	**18193.08**

From the table 3.1, and by testing the autocorrelation and partial autocorrelation to specify p and q, the best ARMA model is (3, 3) with the best AIC equal to 18193.08. Using this order of ARMA, the best ARMA equation [48, 49] for the wind speed data can be constructed as follows,

$$Y(t) = 3.6203 + e_t + [2.038 \times (y_{t-1} - 3.6203)] - [1.3342 \times (y_{t-2} - 3.6203)] + [0.2579 \times (y_{t-3} - 3.6203)] - [0.9279 \times e_{t-1}] + [0.0723 \times e_{t-2}] + [0.1204 \times e_{t-3}] \quad (3.1)$$

Where y_{t-1} is the wind speed value at t-1, e_{t-1} is the error at t-1 and where the mean is equal to 3.6203, and the standard deviation is 0.69087.

After building the ARMA equation, white noise must be generated with mean equal to zero and standard deviation equal to 0.69087. Using ARMA equation and white noise, the forecasted wind speed by ARMA method for one year are shown in Fig. 3.5 below,

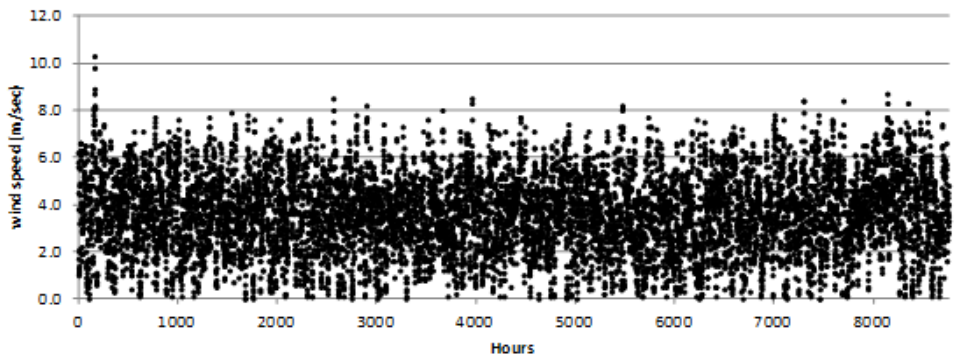


Fig. 3.5: Forecasted Wind Speed for 1 Year by ARMA Method

The trend for the historical wind speed for AL Dhahran 1998, and the trend for the forecasted wind speed by ARMA method for one year are shown in Fig. 3.6 below,

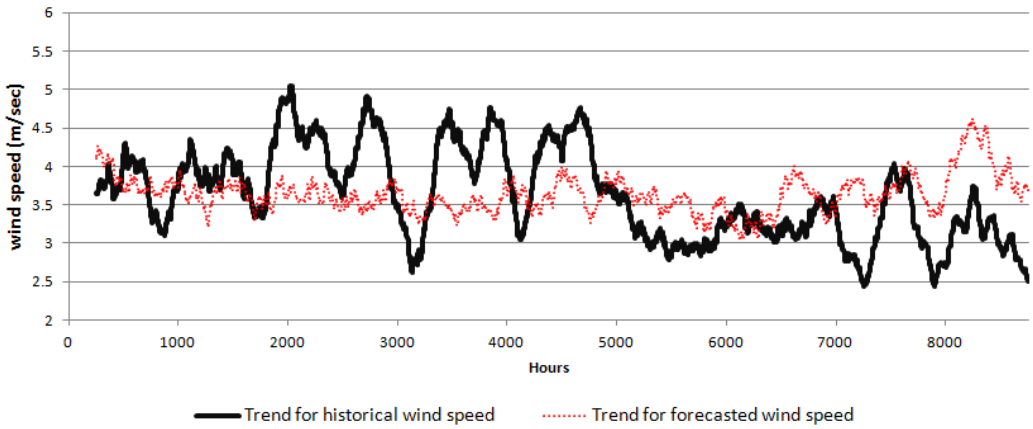


Fig. 3.6: Trend for Historical Wind Speed and Forecasted Wind Speed by ARMA Method for 1 Year

3.1.2 Markov Chain Model

Most practical and physical systems follow the stochastic (or random) process concept in their operational life. The incidents and failures do not follow a deterministic time line and cannot be predicted precisely due to the existence of the random variables in any practical system.

A stochastic process is a group of random variables which characterize a real time process and are interrelated by another variable such as time *t*. Each random variable can have discrete or continues states where the state is the value of the random variable at a particular time and the state space is the set of all possible states.

The stochastic process can be classified based on the type of the state space and time (i.e. if they are discrete or continuous). In power system studies, the discrete state space is considered and the continuous state space is generally not of interest in modeling practical systems.

A Markov chain (MC) is the stochastic model where both the random variable and time index are discrete. In other words, in Markov process, the given condition has a probability in a specific moment, and this probability can be concluded from the information of previous condition. The system of elements that move from one state to another state is known as Markov chain.

A Markov chain is defined by a finite number of discrete states S and a set of transition probabilities p to travel from one state to another in one time step. The probability of transition from state i to state j in one step, Pij is called Transition Probability.

The transition probabilities between all states can be arranged in what's called state transition matrix (STM) where the *Pij* is the probability of the transition from state *i* to state *j* in one time step. The general form of the STM can be arranged as follows:

$$\begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{3.2}$$

State transition matrix (STM)

For k states, and from the frequencies of the states at time t, the state probabilities can be found. If the number of transitions from state i to state j is known as *nij* in the series of data, then the transition probabilities is:

$$p_{ij} = n_{ij} \,/\, \sum_j n_{ij} \tag{3.3}$$

The diagonal elements in this matrix (*p11,p22,…pnn*) are the probabilities to remain in the present state for a time step and all probabilities should be between 0 and 1. Since each row of matrix *P* consists of all the possible probabilities for each state, the sum of all the probabilities in any row is one. This means that the total probabilities of all transitions exiting in the state should equal one (including the probability to remain in the same state).

The states and probabilities can also be represented by the state space diagram (SSD) or state transition diagram (STD). A general STD for a three states model is shown in Fig. 3.7 below.

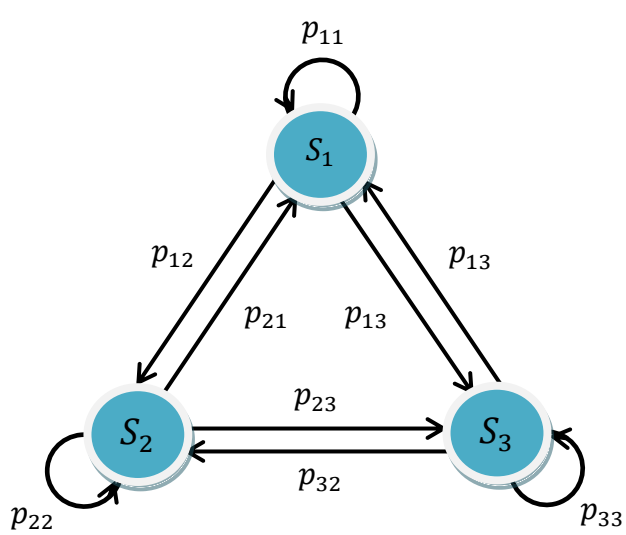


Fig. 3.7: State transition diagram (STD) for three states

The initial probability distribution vector can be calculated as,

$$p(0) = [p_1(0) \quad p_2(0) \quad p_3(0) \ldots . p_n(0)] \tag{3.4}$$

The probability of moving from state *i* to state *j* in *n*-th steps of time can be calculated using the STM as,

$$P^n = PPP \ldots\ldots P \ (n\ times) \tag{3.5}$$

The probability to be in any state after n-th steps of times can be calculated also as the initial probability of each state multiplied by the n-th STM as below,

$$p(n) = p(0)P^n \tag{3.6}$$

When the probability of being in any state after infinite number of steps is independent from the initial probabilities, the system is called ergodic and has steady state probabilities (denoted by the symbol π).

The steady state probability is the probability of being in state i after infinite number of steps and it can be calculated by,

$$\sum_{j=1}^{n} \pi_j = 1 \tag{3.7}$$

To model the wind speed for Dhahran city in the eastern province of Saudi Arabia 1998, and find the forecasted wind speed using the Markov Chain model, the state transition matrix must be found.

After building the transition matrix, the cumulative probability matrix is created, where the cumulative probability refers to the probability that the value of a random variable falls within a specified range.

The steps for Markov modeling and forecasting can be represented in Fig. 3.8 below:

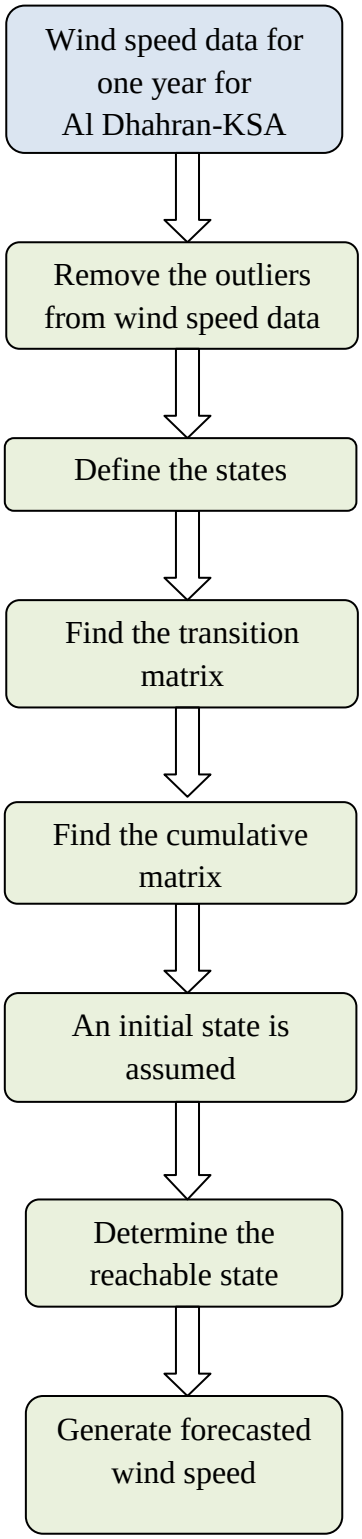


Figure 3.8: Flow Chart for the Methodology Stages in Markov Chain Model

The main steps for the modeling and evaluating process are as follows:

1- Remove the outliers from historical wind speed data.

2- Define the states and the range for each state.

3- Find the transition matrix.

4- The cumulative probability transition matrix is found by taking successive summations of each row of the transition matrix.

5- An initial state is assumed randomly.

6- By using a uniform random number generator, the next state is found when the generated random value is greater than the cumulative probability of the previous state but less than or equal to the cumulative probability of the following state which known as reachable state.

7- A transition from state 'i' to state 'j' in cumulative matrix can be converted into wind speed data by using the following [50]:

$$V = V_{j-1} + R_i(V_j - V_{j-1}) \tag{3.8}$$

Where V_j, V_{j-1} are the lower and upper boundaries of the state and R_i is the uniform random number.

8- By repeating Steps 6 and 7, the desired length of forecasted wind speed data and wind power can be generated.

In order to build the transition matrix, states must be defined according to the maximum and minimum value for the historical wind speed data.

Three states and 93 states models are considered in this research. In the first model with the three states of wind speeds, the outliers are removed before building the state transition matrix. The outlier is considered to be any point that is more than three standard deviations away from the mean as shown in Fig.3.1.

The maximum wind speed is 9.3 m/sec. Therefore, the three states are given as {S1 (0-3.1), S2 (3.1-6.2), S3 (6.2-9.3)}. Then, the number of transitions from one state to another are calculated to get the transition rate and transition probability matrix. The number of transitions and the state transition matrix are shown below in the matrices

$$\begin{bmatrix} 3291 & 520 & 1 \\ 521 & 3427 & 172 \\ 0.00 & 173 & 557 \end{bmatrix}$$

Transitions' number matrix

$$P = \begin{bmatrix} 0.86333 & 0.13641 & 0.00026 \\ 0.12646 & 0.83180 & 0.04174 \\ 0.00000 & 0.23699 & 0.76301 \end{bmatrix}$$

State transition matrix

The sum of all the probabilities in any row is one. Same steps are done with 93 states for the same wind speed data, where each state will be 0.1 m/sec, and the process will be continued on the state transition matrix that will be found. Where the transition matrix with dimension (93x93).

The sparsity pattern image that shows the nonzero elements of the transition matrix with dimension 93x93 is shown in Fig. 3.9 below.

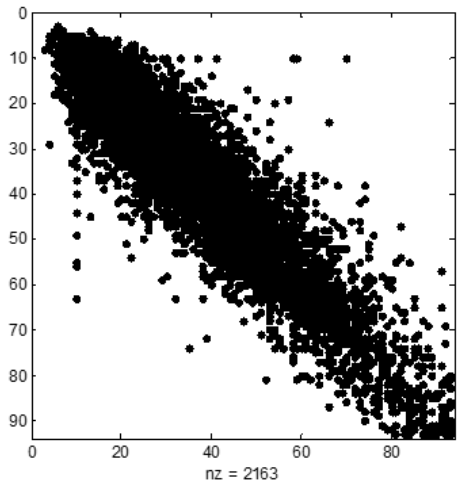


Fig. 3.9: Sparsity pattern of the matrix 93x93

After building the transition matrix, the cumulative matrix will be constructed also with dimension of 93x93, then the initial state will be selected randomly.

By using a random generator, random number (R) will be generated, where the next state is determined when the generated random number is greater than the cumulative probability for the previous state and less than or equal the cumulative value for the next state, where this state is known as reachable state.

And by repeating this step for several times, the forecasted wind speed can be calculated for any number of hours by using the equation (3.8) above.

The forecasted wind speed by Markov Chain method for one year are shown in Fig. 3.10 below,

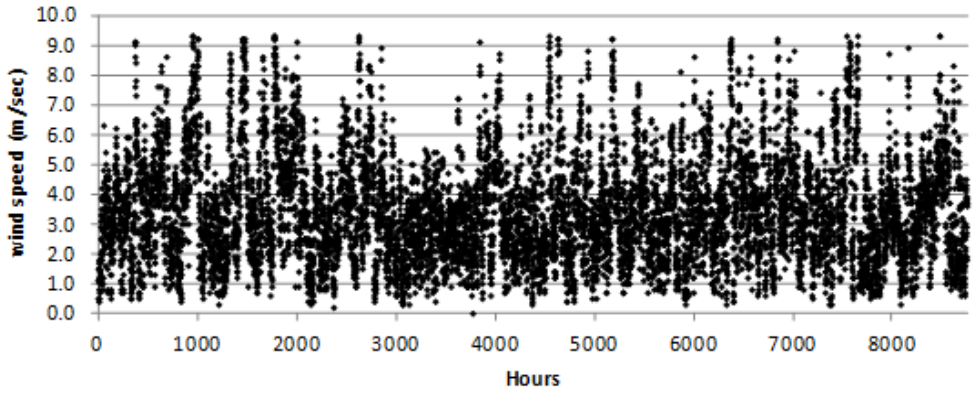


Fig. 3.10: Forecasted Wind Speed for 1 Year by Markov Chain Method

The trend for the historical wind speed for AL Dhahran 1998, and the trend for the forecasted wind speed by Markov Chain method for one year are shown in Fig. 3.11 below,

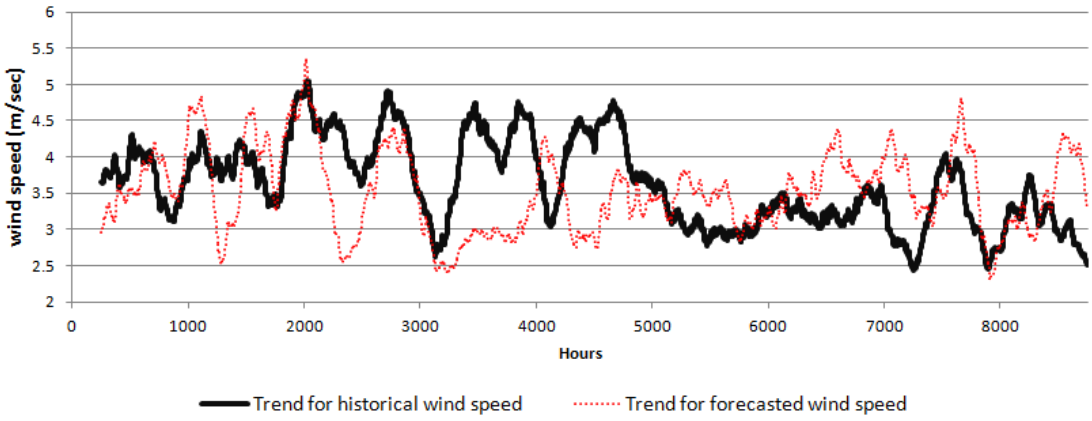


Fig. 3.11: Trend for Historical Wind Speed and Forecasted Wind Speed by Markov Chain Method for 1 Year

3.1.3 Probability Distribution Functions

The probability distribution is a function that assigns probabilities to each value of a random variable. The probability of x can be given as,

$$p(x_i) \geq 0 \tag{3.9}$$

$$\sum_{i=1}^{\infty} p(x_i) = 1 \tag{3.10}$$

Where $p(x_i)$ is defined as the probability mass function that assigns probabilities to all possible outcomes for a discrete random variable.

Cumulative Distribution Function (CDF) is defined as A function that gives a probability that a random variable X takes on value less than or equal to X , as equation 3.11 below:

$$F(x) = \sum_{i=1}^{n} p(x_i) \tag{3.11}$$

The Discrete Probability Distributions are several, like Bernoulli, Binomial, Geometric, Poisson, Uniform, Normal, Weibull, Gamma, Erlang distribution, Extreme Value (Gumbell), Triangular, Log-normal and others distributions.

The data must be transferred to form that is suitable for use in the simulation, this will be done when this data are fitted to some distributions, and this is known as Modeling and Simulating Data with Distributions.

Fitting the distribution to the data is needed to find the appropriate distribution and its suitable parameter like mean and variance that give the best probability to produce the observed data.

Goodness-of-fit tests are needed to determine the appropriate distribution for a given data. The three most popular tests in simulation modeling are, Chi squared, Kolmogorov-Smirnov and Anderson Darling.

These tests are the most popular tests that use goodness of fit statistics to find the best distribution that present the probability of the data. The evaluation is done by note the lowest value of these statistics, which lead to the nearest and best fitted distribution that match the data.

It's not easy to understand the goodness-of-fit statistics, they provide the probability where the fitted distribution is generating random data that have generated a value of goodness of fit as nearest as to the value that is counted for the observed data, not as it's thought that they give a probability measure where the data is actually coming from the fitted distribution.

The values of the distribution's parameters that give the best joint probability to the observed data are known as maximum likelihood estimators.

a) Chi Square Statistic

The measure of the connectivity between the expected frequency of the fitted distributions with the observed data frequency, is known as Chi Square method. The Chi-Square can be given as,

$$\sum_{i=1}^{N} \frac{[O(i) - E(i)]^2}{E(i)} \tag{3.12}$$

Where the observed frequency are O(i), and the expected frequency from the fitted distribution is E(i).

The Chi Square is high sensitive to the large error, because it depends on the sum of the square errors and on the number of bars that are used. If the number of bars changed, the rank between two distributions can be also changed.

b) Kolmogorov Smirnoff Statistic

Kolmogorov Smirnov compares the cumulative frequency of the fitted and observed data. The maximum vertical distance between the cumulative for the observed distribution and the fitted distribution is the core of this statistical method. The Kolmogorov Smirnov distance D_n is defined as,

$$Dn = \max\left[|Fn(x) - F(x)|\right] \tag{3.13}$$

Where *Dn* is known as the Kolmogorov Smirnov distance, n is the total number of data point, F(x) is the distribution function for the fitted data, and Fn(x) = i/n, where i is the cumulative rank of the data point. As shown in Fig.3.12, the value of Kolmogorov Smirnov statistic is determined by the largest difference only.

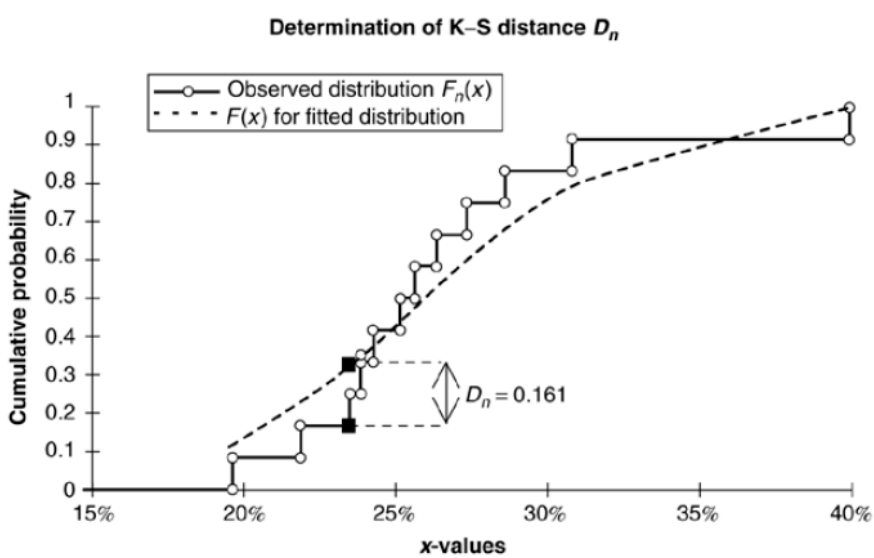


Fig. 3.12: Example of finding Dn value [51]

c) Anderson Darling Statistic

The advanced version of the Kolmogorov Smirnoff is the Anderson Darling method, this is because $\gamma(x)$ compensates the increase of the variance in the vertical distance between the observed and fitted cumulative distributions.

Moreover, f(x) weights the observed distances by the probability that a value will be generated at that *x*-value, in addition, the vertical distances are integrated over all values of *x* to make maximum use of the observed data, where in Kolmogorov Smirnov only looks at the maximum vertical distance.

For these reasons, it's more useful to use Anderson Darling than Kolmogorov Smirnov.

The Anderson Darling is given in the equations 3.14 and 3.15 below.

$$A_n{}^2 = \int_{-\infty}^{\infty} |F_n(x) - F(x)|^2 \, \gamma(x) f(x) dx \tag{3.14}$$

$$\gamma(x) = \frac{n}{F(x)[1-F(x)]} \tag{3.15}$$

Where n is the total number of data point, F(x) and f(x) are the distribution and density function for the fitted distribution, respectively. Fn(x) = i/n, where i is the cumulative rank of the data point.

From previous discussion, it can be concluded that the best two methods that can give the best distribution which can represent the observed wind speed data are Anderson Darling and Chi Square.

Therefore, the equation that relates between these two methods to give the goodness of fit index can be defined as,

$$GOF = (0.6*\text{A-Darling value}) + (0.4*\text{Chi-Square value}) \tag{3.16}$$

After finding the best distribution that represents the historical wind speed data for AL Dhahran 1998, states can be constructed. The states will cover the range of wind speeds between the minimum and the maximum historical wind speed data.

Then, the transition matrix and cumulative matrix are found, where each transition will not be more than two steps from each state. Finally, the forecasted process can be started.

The steps for Pdf modeling and forecasting can be represented in Fig. 3.13 below:

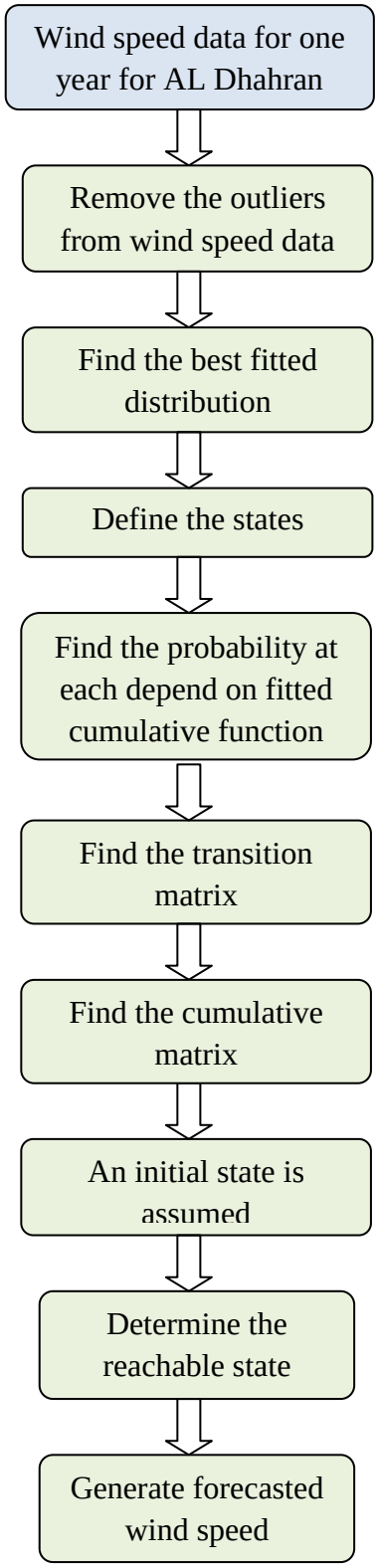


Figure 3.13: Flow Chart for the Methodology Stages in Pdf Model

The main steps for the modeling and evaluating process are as follows:

1- Remove the outliers from historical wind speed data.

2- Find the best fitted distribution function.

3- Define the states and the range for each state.

4- Find the probability at each state depend on fitted cumulative function.

5- Find the transition matrix.

6- The cumulative probability transition matrix is found by taking successive summations of each row of the transition matrix.

7- An initial state is assumed randomly.

8- By using a uniform random number generator, the next state is found when the generated random value is greater than the cumulative probability of the previous state but less than or equal to the cumulative probability of the following state which known as reachable state.

9- A transition from state 'i' to state 'j' in cumulative matrix can be converted into wind speed data by using the following [50]:

$$V = V_{j-1} + R_i(V_j - V_{j-1}) \tag{3.8}$$

Where V_j, V_{j-1} are the lower and upper boundaries of the state and R_i is the uniform random number.

10- By repeating Steps 8 and 9, the desired length of forecasted wind speed data and wind power can be generated.

The observed wind speed data for Al Dhahran is fitted using different probability distribution functions. First, the outliers are removed from the wind speed data, where outliers being defined as the data points that diverge from the population by three standard deviations as shown in Fig. 3.1. The wind speed data are then modeled and tested by two different goodness-of-fit statistical methods, Anderson-Darling and chi-square. Finally, these values are normalized and equation (3.16) is used to calculate the goodness-of-fit index (GOF Index). Table 3.2 shows the goodness-of-fit values for several distributions.

TABLE 3.2: Normalized Statistics Values for Several Distributions

Function	Normalized Anderson-Darling Value	Normalized Chi-Square Value	GOF Index
Extreme value	1.00	1.00	1.000
Generalized extreme value	0.03	0.009	0.020
Logistic	0.16	0.142	0.155

As shown in Fig. 3.14, the best fitted distribution is Generalized extreme value distribution, where it has the least GOF index.

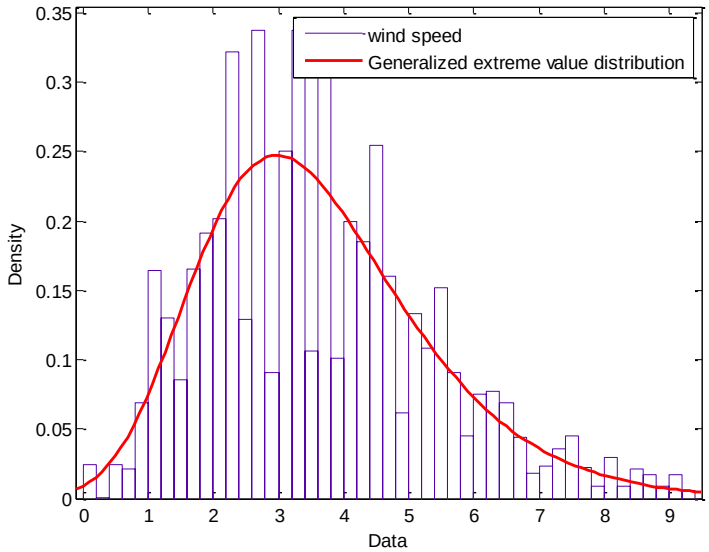


Fig. 3.14: Observed and Fitted Wind Speed Data Using Generalized Extreme Value Distribution

By determine the best fitted distribution, the states must be defined depend on the maximum and minimum value for the historical wind speed data.

16 states model of the wind speed data is considered in this research for Pdf method. The maximum wind speed is 9.3 m/sec; therefore, 16 states will be constructed with the range of 0.62 m/sec for each state.

After defining the states, the probability at each state must be calculated depend on the Generalized extreme value cumulative function, where the cumulative probability for the Generalized extreme value is shown in Fig. 3.15 below,

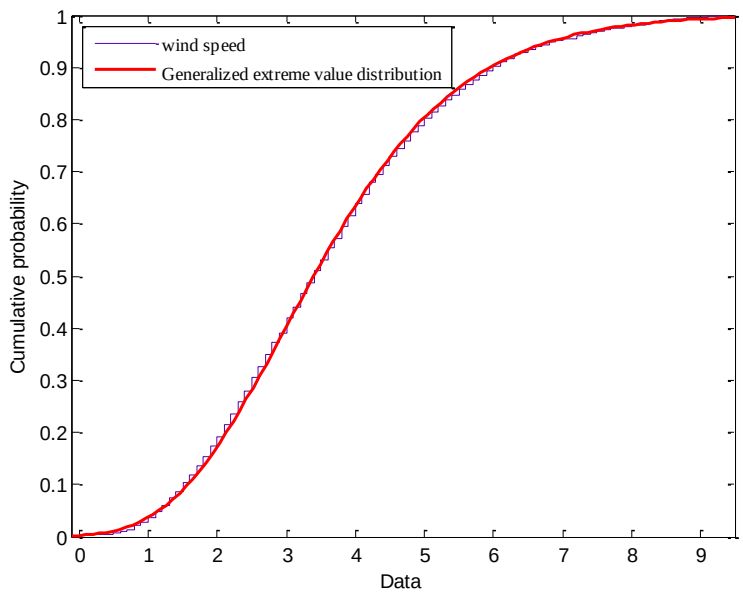


Fig. 3.15: Cumulative Probability for Generalized Extreme Value Distribution

Then, the number of transitions from one state to another are calculated to get the transition rate and transition probability matrix. Where the transition matrix with dimension (16x16).

The sparsity pattern image that shows the nonzero elements of the transition matrix with dimension 16x16 is shown in Fig. 3.16 below.

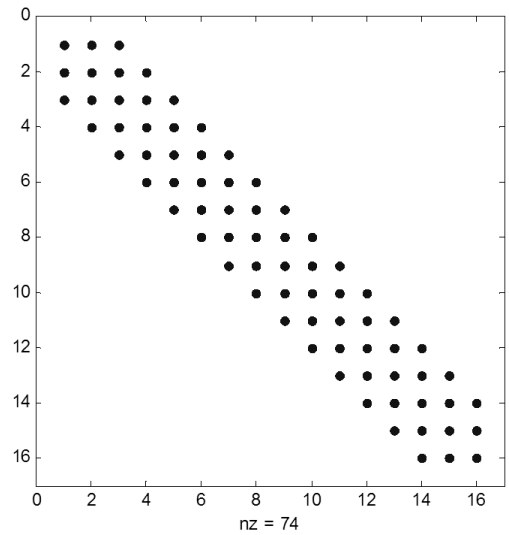


Fig. 3.16: Sparsity pattern of the matrix 16x16

After building the transition matrix, the cumulative matrix will be constructed also with dimension of 16x16, then the initial state will be selected randomly.

By using a random generator, random number will be generated, where the next state is determined when the generated random number is greater than the cumulative probability for the previous state and less than or equal the cumulative value for the next state, where this state is known as reachable state.

And by repeating this step for several times, the forecasted wind speed can be calculated for any number of hours by using the equation (3.17) above.

The forecasted wind speed by Pdf method for one year are shown in Fig. 3.17 below,

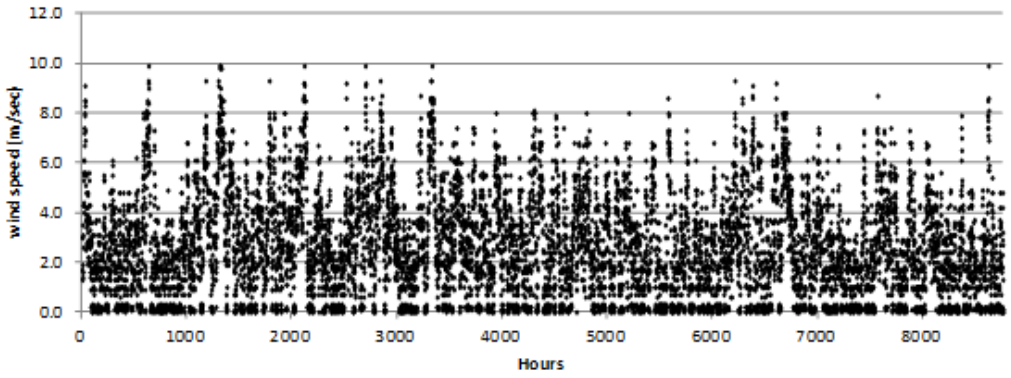


Fig. 3.17: Forecasted Wind Speed for 1 Year by Pdf Method

The trend for the historical wind speed for AL Dhahran 1998, and the trend for the forecasted wind speed by Pdf method for one year are shown in Fig. 3.18 below,

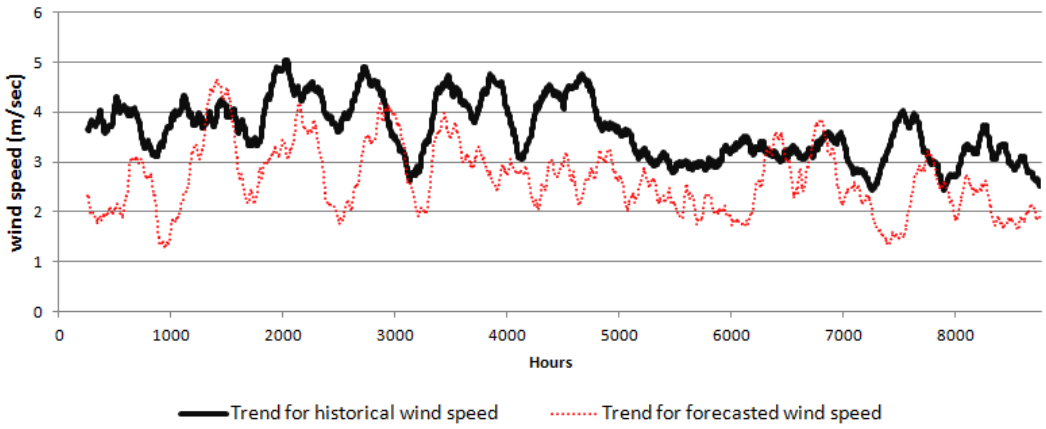


Fig. 3.18: Trend for Historical Wind Speed and Forecasted Wind Speed by Pdf Method for 1 Year

3.2 Modeling and Forecasting Wind Power

To find the power output of the Wind Turbine Generator (WTG), the relationship between wind speed and WTG's power output will be utilized. The power output for each unit can be calculated based on wind speed and by using the manufacturer's

specifications. The forecasted wind power is obtained directly from predicted wind speeds through a certain power curve depending on the size of turbines.

Using the forecasted wind speed in the three methods, the wind power can be simulated using the speed-power curve for a 100 KW turbine [52]. The rated speed for this turbine is equal to 9.5 m/sec and the cut-in speed is equal to 2.2 m/sec. The specification sheet for the turbine used in this study is shown in Fig. 3.19.

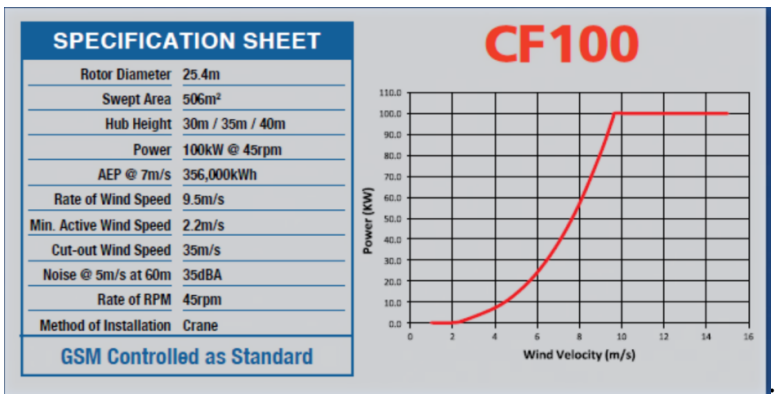


Fig. 3.19: Specification Sheet for the Wind Turbine Used in This Study [52]

The following equation is used to calculate the forecasted power output for each given wind speed.

$$P = 0.5*\rho*A*V^3*C_p \tag{3.18}$$

Where the ρ is the air density which equal 1.18 kg/m3, C is the coefficient of performance which equal 0.4, V is the velocity of the wind, and A is the frontal area which equal 506.4506 m^2. The forecasted wind power will be calculated from the forecasted wind speed in the three methods, ARMA, Markov Chain, and Pdf.

The relation between forecasted wind speed and forecasted wind power from ARMA method for 10 years is shown in Fig. 3.20 below,

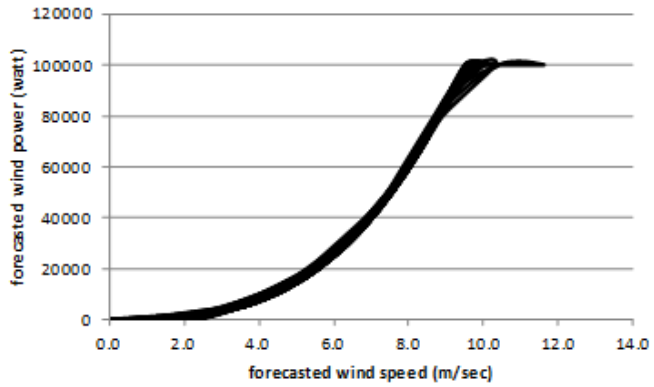


Fig. 3.20: Forecasted Wind Speed and Forecasted Wind Power by ARMA method for 10 years

The trend for the historical wind power for AL Dhahran 1998, and the trend for the forecasted wind power by ARMA method for one year are shown in Fig. 3.21 below,

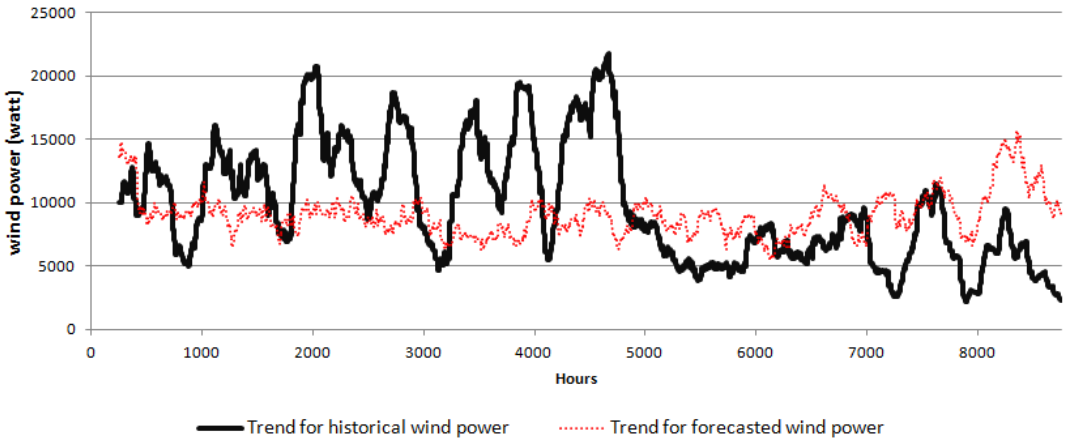


Fig. 3.21: Trend for Historical wind Power and Forecasted Wind Power by ARMA Method for 1 Year

The relation between forecasted wind speed and forecasted wind power from Markov Chain method for 10 years is shown in Fig. 3.22 below,

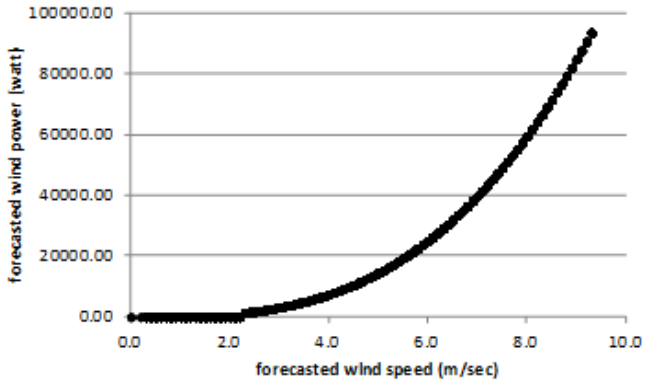


Fig. 3.22: Forecasted Wind Speed and Forecasted Wind Power by Markov Chain method for 10 years

The trend for the historical wind power for AL Dhahran 1998, and the trend for the forecasted wind power by Markov Chain method for one year are shown in Fig. 3.23 below,

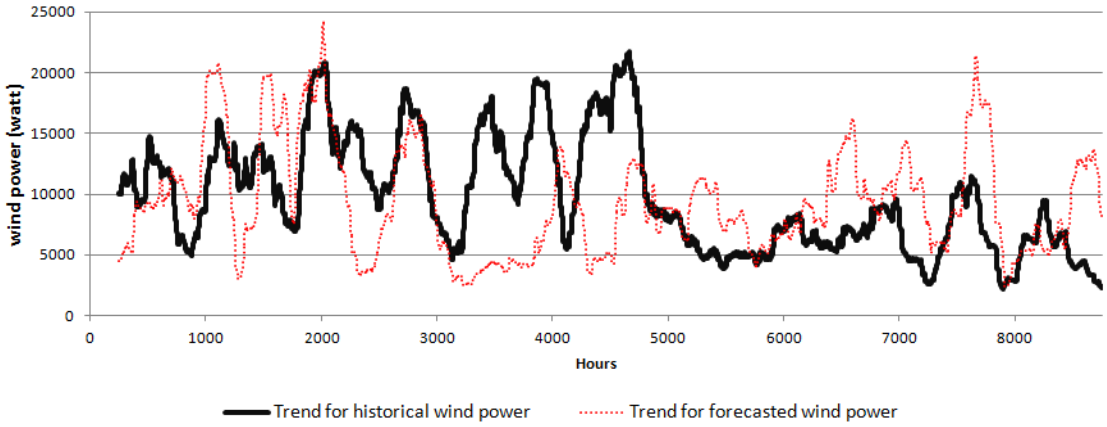


Fig. 3.23: Trend for Historical wind Power and Forecasted Wind Power by Markov Chain Method for 1 Year

The relation between forecasted wind speed and forecasted wind power from Pdf method for 10 years is shown in Fig. 3.24 below,

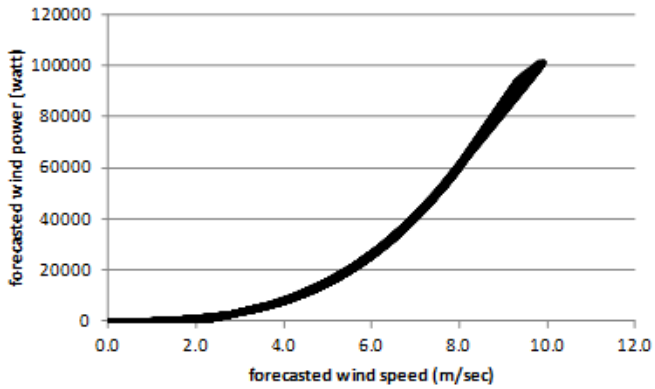


Fig. 3.24: Forecasted Wind Speed and Forecasted Wind Power by Pdf method for 10 years

The trend for the historical wind power for AL Dhahran 1998, and the trend for the forecasted wind power by Pdf method for one year are shown in Fig. 3.25 below,

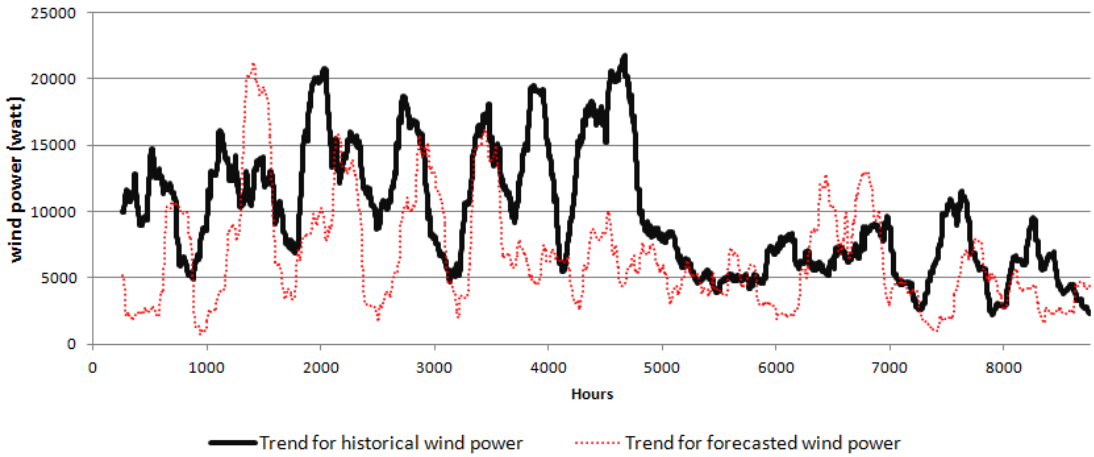


Fig. 3.25: Trend for Historical wind Power and Forecasted Wind Power by Pdf Method for 1 Year

3.3 Comparison Analysis

Two measures are used in this research to compare between the historical and forecasted wind speed and power. The two measures are: the root mean square error (RMSE) and the mean absolute deviation (MAD).

For more realistic, herein, wind speed data for AL Dhahran area- KSA in 2013 is collected and used as a historical data for validating the goodness of fit for the forecasted wind speed and power.

3.3.1 Root Mean Square Error

The RMSE is used to calculate the deviation between the forecasted and actual values, as shown in eq. (3.19) below,

$$RMSE = \left[\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}\right]^{0.5} \tag{3.19}$$

Where x's for the actual values, y's for the forecasted values, and n for the number of dataset. Where the lowest RMSE value means more accurate forecasted values comparing with the actual data, which also determine the more accurate modeling and forecasting method.

3.3.2 Mean Absolute Deviation

The MAD calculate the mean for the absolute deviation between the forecasted values and actual values, as shown in eq. (3.20) below,

$$MAD = \frac{\sum_{i=1}^{n}|m_i - d_i|}{n} \tag{3.20}$$

Where m is the mean at each point i for the forecasted values, d is the mean at each point i for the actual values, and n for the number of dataset. Also, the lowest MAD value means more accurate forecasted values comparing with the actual data, which also determine the more accurate modeling and forecasting method.

3.3.3 Comparison Results

By testing the three data sets (i.e. ARMA, Markov Chain, and Pdf) of forecasted wind speed and power for AL Dhahran- KSA, the comparison results show that ARMA method gives the best represented forecasted wind speed and power, which mean that the most accurate forecasted wind speed and power are generated by ARMA method, as shown in table 3.3 below.

Table 3.3: Comparison Results Between Predicted And Historical Wind Speed And Wind Power For Al Dhahran

comparison for 10 years data	**Wind Speed**		**Wind Power**	
	RMSE	**MAD**	**RMSE**	**MAD**
ARMA	2.95	2.31	28406	18258
Markov	2.99	2.34	29588	18985
pdf	3.65	2.95	30590	19647
comparison for 1 year data	Wind Speed		Wind Power	
	RMSE	**MAD**	**RMSE**	**MAD**
ARMA	2.88	2.25	27956	17832
Markov	3.05	2.40	29853	19225
pdf	3.61	2.90	30363	19368

CHAPTER 4

DISTRIBUTION SYSTEM RELIABILITY CALCULATIONS

4.1 Evaluation of Distribution System Reliability

Reliability is an important issue in any designed system or product. Customers and users do not expect any failure or interruption of the service since the failure can be expensive or insecure. It is important to differentiate between the power quality and system reliability.

System reliability is more concerned with the continuity of the service (sustained and momentary interruptions), whereas power quality pertains to other power problems such as voltage fluctuations, harmonic distortion, and variations in the wave shape or magnitude.

In practice, system average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI) are two commonly used indices used to evaluate the frequency and duration of the interruptions that customers experience in the period of study (typically one year). These two indices are related to the configuration of a system and the probability of each component in the system to fail.

The indices are used in reliability evaluation to study the effect of components on reliability and to compare different configurations based on their reliability performance. One important route to the examination of reliability relates to the probabilistic modeling

of networks and systems in general. For example, Billinton has employed the basic properties of the probability of failure of components in series and parallel (including vector-matrix operational analysis) to quantify the probability of failure of a system or network.

In order to response to real changes, the major events are usually excluded in the reliability calculations, such as weather. One way to define the major event is when the event leads 10% of the customers lose the service for 24 hours.

In this research, the two major reliability indices that will be studied are the SAIDI and the SAIFI [53],

$$SAIDI = \frac{Total\ duration\ of\ all\ interruptions}{Total\ number\ of\ customers\ connected}\ (\mathrm{hr/cstmr\ yr}) \quad (4.1)$$

$$SAIFI = \frac{Total\ number\ of\ all\ interruptions}{Total\ number\ of\ customers\ connected}(\mathrm{intrp/cstmr\ yr}) \quad (4.2)$$

The SAIFI defines the frequency of the outages for each customer, and the SAIDI define the duration of the outages for each customer in one year.

Weather outages and planned outages like maintenance are usually excluded from the reliability indices because the utility can’t control these incidents.

4.2 Theoretical Concepts for Reliability Calculation

Even though availability and reliability are used interchangeably in several studies, they are not the same in concept and values. The reliability basically represents the probability that a component or a system will perform its designed function without any failure under

the normal working environment. The reliability does not reflect or contain any time to repair the failed component. It mainly reflects how long the system is expected to work at a specific time before it fails.

The availability, on the other hand, is the probability that the component or the system is working as expected during its operational cycle. It shows how share of time the system is working. Availability depends on both the expected time to fail and time to repair the component or the system. The availability is,

$$Avaliability = \frac{UP\ TIME}{UP\ TIME + DOWN\ TIME} \tag{4.3}$$

The reliability will be used in this research to represent availability, unavailability, failure frequency and failure duration. In another words, the probability where at least one minimal set of the components is working between the input and the output is known as the system reliability.

The life of the system components can be divided into three intervals: useful life, infant mortality, and the wear out. The period where the reliability evaluation is calculated is known as the useful period.

In this research, all components are assumed as repairable, which mean if the component failed, it can be replaced by a new component with same failure rate. Mean time to fail (MTTF) or (T_f) is the time that each component takes to fail, and the mean time to repair (MTTR) or (T_r) is the time that each component takes to repair, but, these definitions are used when each component has only up and down states. The mean time between failures

(MTBF) or the mean cycle time (T_{fr}) is the time that each component takes to fail and to repair.

$$\text{MTBF} = \text{MTTF} + \text{MTTR}$$

$$T_{fr} = T_f + T_r \tag{4.4}$$

And the mean failure frequency (f) can be defined [15],

$$f = \frac{1}{MTBF} = \frac{1}{MTTF + MTTR} \tag{4.5}$$

The availability (A) is the probability of the component to be in the work state, and if the component in the down state so this probability is called unavailability (U), the relations between A, U with MTTR, MTTF are shown below [54],

$$A = \frac{MTTF}{MTBF} = \frac{MTTF}{MTTF + MTTR} \tag{4.6}$$

$$U = \frac{MTTR}{MTBF} = \frac{MTTR}{MTTF + MTTR} \tag{4.7}$$

The average interruption frequency (AIF) is the frequency of outages for the component in one year, while the average interruption duration (AID) is the duration of outages for the component in one year.

In another word, AIF can be defined as the number of failures for the component in one year as mentioned below [55],

$$AIF_i = 8760f = \frac{8760}{MTTF + MTTR} \tag{4.8}$$

Also, AIF can be defined as the duration for all failures in hours for the component in one year as mentioned below [55],

$$AID_i = 8760U_i = (MTTR)(AIF_i) \tag{4.9}$$

Another definition is (FD) or failure duration, which can be defined as the average duration for a single failure. Also, energy not supplied (ENS) in the failure duration is an important index as mentioned below [53],

$$FD_i = \frac{AID_i}{AIF_i} \tag{4.10}$$

$$ENS_i = AID_i P_{avg}^i \tag{4.11}$$

Where the average annual power is denoted by P_{avg}^i for the bus i.

The availability for two components in series can be defined as equation (4.12), where the system is working if both components are working, and the system will fail if one of them fails [56].

$$A_{sys} = A_1 A_2 = \frac{T_{f1}}{T_{f1} + T_{r1}} \frac{T_{f2}}{T_{f2} + T_{r2}} \tag{4.12}$$

While, if the two components are parallel, so, the unavailability can be defined as equation (4.13), where the system will fail if the two components fail together [56].

$$A_{sys} = 1 - U_1 U_2 = 1 - \frac{T_{r1}}{T_{f1} + T_{r1}} \frac{T_{r2}}{T_{f2} + T_{r2}} \tag{4.13}$$

The frequency of failure for two components in series can be expressed as follow [56],

$$f_s = f_1 + f_2 \tag{4.14}$$

The equivalent frequency for an assumption where if the first components has failed then the second component cannot fail, and this can be expressed as follow [56],

$$f_s = f_1 A_2 + f_2 A_1 = \frac{T_{f1} + T_{f2}}{(T_{f1} + T_{r1})(T_{f2} + T_{r2})} \tag{4.15}$$

The equivalent failure cycle period, equivalent time to fail, and equivalent time to repair can be calculated as follow [55],

$$T_{frs} = \frac{1}{f_s} = \frac{1}{f_1 A_2 + f_2 A_1} \tag{4.16}$$

$$T_{fs} = A_s T_{frs} = \frac{T_{f1} T_{f2}}{T_{f1} + T_{f2}} \tag{4.17}$$

$$T_{rs} = U_s T_{frs} = \frac{(T_{f1} + T_{r1})(T_{f2} + T_{r2}) - T_{f1} T_{f2}}{T_{f1} + T_{f2}} \tag{4.18}$$

For the two components in parallel, the frequency of failure is calculated as follow [56],

$$f_p = f_1 U_2 + f_2 U_1 \tag{4.19}$$

Table 4.1 below shows the result where the system is 100% reliable, it also shows the exact formulas for T_f^{eq} and T_r^{eq} , and the formulas for the approximation case where $T_f >> T_r$.

Table 4.1: T_f^{eq} and T_r^{eq} for the Components in Series and Parallel [55]

		T_f^{eq}	T_r^{eq}
Approximate Formulas $T_r << T_f$	*Series*	$\frac{T_{f1}T_{f2}}{T_{f1}+T_{f2}}$	$\frac{T_{r1}T_{f2}+T_{r2}T_{f1}}{T_{f1}+T_{f2}}$
	Parallel	$\frac{T_{f1}T_{f2}}{T_{r1}+T_{r2}}$	$\frac{T_{r1}T_{r2}}{T_{r1}+T_{r2}}$
Exact formulas	*Series*	$\frac{T_{f1}T_{f2}}{T_{f1}+T_{f2}}$	$\frac{(T_{f1}+T_{r1})(T_{f2}+T_{r2})-T_{f1}T_{f2}}{T_{f1}+T_{f2}}$
	Parallel	$\frac{T_{r1}T_{f2}+T_{r2}T_{f1}+T_{f1}T_{f2}}{T_{r1}+T_{r2}}$	$\frac{T_{r1}T_{r2}}{T_{r1}+T_{r2}}$

By using the results in table 4.1, the equivalent AID and AIF seen by the receiving bus for the components in parallel and in series with $T_f >> T_r$ can be expressed as table 4.2 below,

Table 4.2: AIF^{eq} and AID^{eq} as a Function of AID and AIF of each component [55]

	Series	Parallel
AIF^{eq}	$AIF_1 + AIF_2$	$\frac{AID_1AIF_2 + AID_2AIF_1}{8760}$
AID^{eq}	$AID_1 + AID_2$	$\frac{AID_1AID_2}{8760}$

The system average interruption frequency index (SAIFI) can be found by Eq. (4.20) below. While the system average interruption duration index (SAIDI) can be found by Eq. (4.21) below [55].

$$SAIFI = \frac{\sum_{i=1}^{B} AIF_i N_i}{N_T} \tag{4.20}$$

$$SAIDI = \frac{\sum_{i=1}^{B} AID_i N_i}{N_T} \tag{4.21}$$

Where N_i is the total number of customers connected to a given bus i, N_T is the total number of customers in the system, and B is the total number of buses.

4.3 Distribution System Reliability Evaluation by Markov Models

There are different states in any power system, the availability, MTTF, interruption duration and frequency for each load can be found by the reliability evaluation. It is important to define which state is up (working) if there is a connection between the load and the source, and which state is down (outage) if the link between the load and the source is disconnected, then the MTTF, steady state probability, duration, and frequency can be calculated by using Markov model.

The number of failures divided by the total working time per year is called the failure rate (λ), and it can be defined as the transition from up state to down state. The number of repairs divided by the total outages time is called the repair rate (μ), and it can be defined as the transition from down state to up state.

If the number of components in the system is n, so 2^n is the number of states, as an example, in n=2, the number of states is 4, {S_1= 11, S_2= 10, S_3= 01, S_4= 00 }. The state transition matrix (STM) for the two components system are shown in Fig. 4.1.

$$\sigma = \begin{bmatrix} 0 & \lambda_2 & \lambda_1 & 0 \\ \mu_2 & 0 & 0 & \lambda_1 \\ \mu_1 & 0 & 0 & \lambda_2 \\ 0 & \mu_1 & \mu_2 & 0 \end{bmatrix}$$

Fig. 4.1: STM for the two components system

4.3.1 Calculating Reliability Using Markov Models

After building the transition rate matrix (σ-matrix), the stochastic probability matrix (P- matrix) must be constructed as below [56]:

$$P = \begin{bmatrix} 1-\sum_{j=2}^{n}\rho_{1j} & \rho_{12} & \dots & \rho_{1n} \\ \rho_{21} & 1-\sum_{\substack{j=1\\ j\neq 2}}^{n}\rho_{2j} & \dots & \rho_{2n} \\ \vdots & \vdots & \dots & \vdots \\ \rho_{n1} & \rho_{n2} & \dots & 1-\sum_{j=1}^{n-1}\rho_{nj} \end{bmatrix} \tag{4.22}$$

Then, the Markov differential equation below can be solved in order to find the time dependent probabilities [56].

$$\begin{bmatrix} -\sum_{j=2}^{n}\sigma_{1j} & \sigma_{21} & \dots & \sigma_{n1} \\ \sigma_{12} & -\sum_{\substack{j=1\\ j\neq 2}}^{n}\sigma_{2j} & \dots & \sigma_{n2} \\ \vdots & \vdots & \dots & \vdots \\ \sigma_{1n} & \sigma_{2n} & \dots & -\sum_{j=1}^{n-1}\sigma_{nj} \end{bmatrix} \begin{bmatrix} P_1(t) \\ P_2(t) \\ \vdots \\ P_n(t) \end{bmatrix} = \begin{bmatrix} P_1^{'}(t) \\ P_2^{'}(t) \\ \vdots \\ P_n^{'}(t) \end{bmatrix} \tag{4.23}$$

From (σ-matrix) which gives the transition rates, the coefficient matrix Q can be constructed. By solving the Markov differential equations as below conditions show in Eq. (4.24) and Eq. (4.25), the steady state probabilities can be found [56].

$$Q \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} = 0 \tag{4.24}$$

$$\sum_{j=1}^{n} P_j = 1 \tag{4.25}$$

In Eq. (4.26) below, the last row of Q, P and $\dot{P}$ is substituted with the sum of all probabilities which is equal to one [56].

$$\begin{bmatrix} -\sum_{j=2}^{n}\sigma_{1j} & \sigma_{21} & \dots & \sigma_{n1} \\ \sigma_{12} & -\sum_{\substack{j=1 \\ j\neq 2}}^{n}\sigma_{2j} & \dots & \sigma_{n2} \\ \vdots & \vdots & \dots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}. \tag{4.26}$$

By solving Eq. (4.26), the steady state probabilities can be found for all the states, then the probabilities of the states where the system is up can be added together to calculate the availability of the system, and the probabilities of the states where the system is down can be added together to calculate the unavailability of the system.

The fundamental matrix (N) can be found in Eq. (4.27), where N is the number of steps (average time) that the system takes before entering the absorb state. And (S) can be formed by deleting all the rows and columns associated with the absorbing states from P.

$$N = [I - S]^{-1} \tag{4.27}$$

If the system is repairable, then there are no absorbing states, so, the down states can be defined as absorbing states in order to find the average time before entering the down states or failure states and this is called as MTTF. Also, the up states can be defined as absorbing states in order to find the average time to leave the failure state and enter up state and this called as MTTR.

The expected time to stay in a state i can be found by considering all other states as absorbing states, then the expected frequency for the state can be calculated by multiplying the rates of remove from the state by the probability of being in this state, as expressed in Eq. (4.28) below [56],

$$f_i = P_i \sum_{j=2}^{n} \sigma_{ij} \tag{4.28}$$

4.3.2 Merging of States

The availability and unavailability can be calculated by founding the steady state probabilities by solving the Markov coefficient matrix, where the (A) is founded by adding all up states, and the (U) is founded by adding all down states [56].

$$A = P_{up} = \sum_{i=1}^{u} P_i \qquad\qquad U = P_{down} = \sum_{i=1}^{d} P_i \tag{4.29}$$

Where u is the number of up states, and d is the number of down states.

To combine all down state into a single state, the frequencies of the states are added together excluding any cross occurrence between them, and in this way, the failure frequency can be found by finding the frequency of occurrence of all the down states.

The combined frequency is shown below in Eq. (4.30) for two down states [15].

$$f_m = f_i + f_j - f_{ij} - f_{ji} \tag{4.30}$$

In order to find the frequency of combines down states, the transition matrix is changed, where any cross transition rates between the down states are removed. Then, the steady state probabilities are used with the modified matrix to find this frequency.

The frequency for the down state, and the system failure frequency can be calculated as Eq. (4.31), and Eq. (4.32) below [15].

$$f_i = P_i \sum_{j=2}^{n} \sigma'_{ij} \tag{4.31}$$

$$f_{system} = \sum_{i=1}^{d} f_i \tag{4.32}$$

Where i is the number of down states, and σ'_{ij} is the transition rate from the down state to the up.

4.3.3 Equivalent Series and Parallel Models

Power distribution system is either a radial or meshed network. Radial distribution systems consist of a group of components that connected in series. However, this is not always the case, distribution systems could have parallel or meshed connections in order to improve the performance of the system during any failure or contingency. Each case has its own equations or models to evaluate the reliability. There are several methods for computing the reliability indices, such as approximate method for series and parallel systems, Markov model, etc. [42] [43].

The MTTF for the two components in series can be found by adding the failure rates for these components. The equivalent failure rate (λ_s) and the equivalent repair rate (μ_s) can be expressed as below [56],

$$\lambda_s = \lambda_1 + \lambda_2 \tag{4.33}$$

$$\mu_s = \frac{(\lambda_1 + \lambda_2)(\mu_1 \mu_2)}{\lambda_1 \lambda_2 + \lambda_1 \mu_2 + \lambda_2 \mu_1} \tag{4.34}$$

While, for the two components in parallel, the equivalent failure rate (λ_s) and the equivalent repair rate (μ_s) can be expressed as below [56],

$$\mu_p = \mu_1 + \mu_2 \tag{4.35}$$

$$\lambda_p = \frac{(\lambda_1\lambda_2)(\mu_1 + \mu_2)}{\mu_1\mu_2 + \lambda_1\mu_2 + \lambda_2\mu_1} \tag{4.36}$$

CHAPTER 5

DISTRIBUTED GENERATIONS INTEGRATION

5.1 Distributed Generations Applications in Distribution Systems

DG is defined as a small scale generation unit that is installed in the distribution system and typically connected at substations, on distribution feeders, or at the customer load level. DG differs fundamentally from the traditional model of central generation as it can be located near end-users within an industrial area, inside a building, or in a community.

DG units vary in size, fuel type, and efficiency, and they can be associated with two technologies, conventional energy technology and renewable energy technology. Technologies that utilize conventional energy resources include reciprocating engines, combustion turbines, micro-turbines, and fuel cells. Conversely, renewable energy resources are based on different forms of natural resources such as heat and light from the sun, the force of the wind, and the combustion value of organic matter.

The main difference between the renewable and conventional resources is that the output of the renewable resources depends on variable inputs such as wind or solar energy. The power produced from renewable resources may fluctuate more, making it difficult forecast. In the case in which a DG is connected to the local load to supply the load during interruptions, the demand and supply may not match, especially if the DG is renewable. In this case, the DG is either disconnected due to the activation of the

frequency or voltage protection devices or the system will shed some loads and only supply critical loads.

The DG can be used as a backup generator, where it will be used so supply the load if the main source fails to supply it. It can also be used as a base load generator which is used by the customers to supply a portion of the electricity needs in parallel with the electric power system. The backup DG is integrated to the local load, and the switch is installed on the feeder side of the distributed generation, this manual or automatic switch will be closed and the DG starts to supply the load when the faults happen on the main feeder.

To assess the reliability of the electric microgrids including DG, different tasks should be executed as shown in the flow chart in Fig. 5.1. The proposed algorithm to model the wind speed and investigate the impact of the wind speed models on the reliability of microgrids can be summarized in the following steps:

1- Wind speed is modeled and forecasted using three models, ARMA, Markov, and pdf.
2- Wind power is simulated using the WTG speed-power curve.
3- Renewable power and the demand of different types of customers are simulated.
4- The adequacy transition rate for each type of DG and demand is calculated.
5- The reliability of the microgrid's connection is evaluated using the encoded Markov cut set (EMCS) algorithm [57].
6- Renewable DG are integrated into the system including the DG probability to switch/start and the DG mechanical failure and repair rates.
7- Calculate the load and system reliability indices.

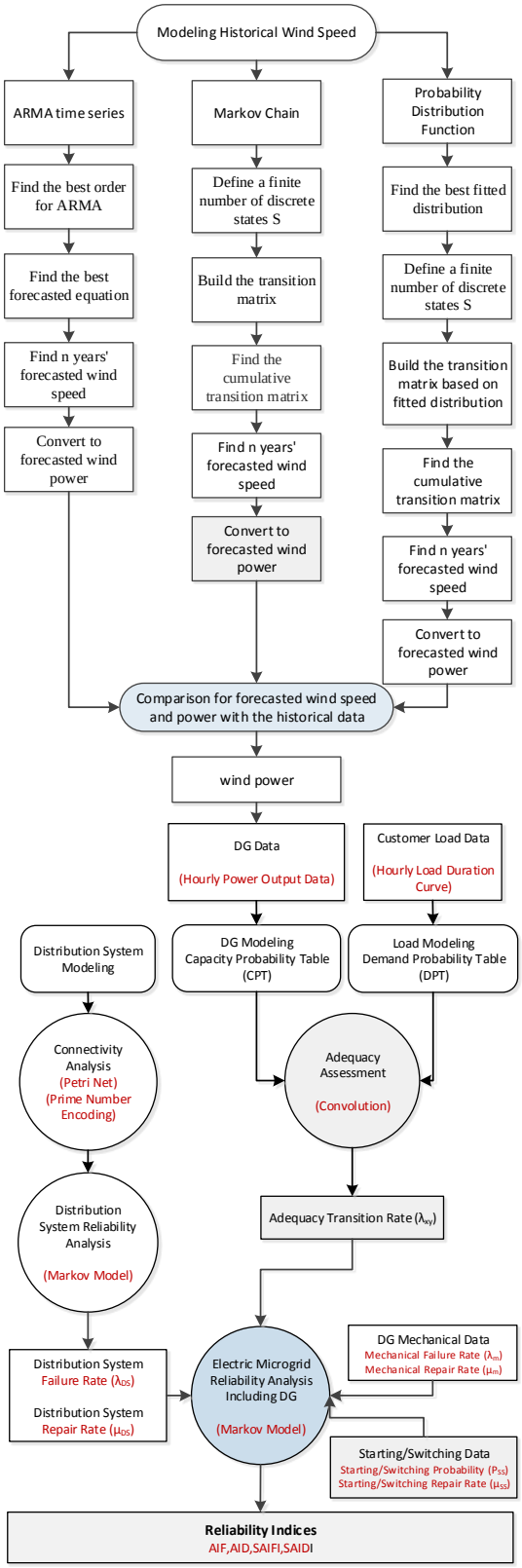


Fig. 5.1: Flow Chart for Reliability Analysis

5.2 DG Reliability Evaluation

Adding DG on the customer side will effect on the customer's reliability, where the reliability will be increased by supplying the load during the interruptions. The duration of the outages are expected to be fewer by adding DG at the load bus. When evaluating the reliability effect of the DG on the load, several factors must be considered, like the power output, failure rate, repair rate, and the starting time.

In the renewable resources, the DG may not be able to supply the total demand during the interruption due to the capacity and the availability of the DG.

In the future distribution system, there will be more integration of DGs at the local load, but the DG usually has smaller capacity to load ratio, and this ratio may limit the availability of the distributed generation during the interruption since the probability of the local load demand to be more than the output of the DG is high.

In the normal condition the load will be supplied by the utility, and the DG will supply the load in an islanded operation if the distribution system fails to supply the load, as shown in Fig. 5.2 below,

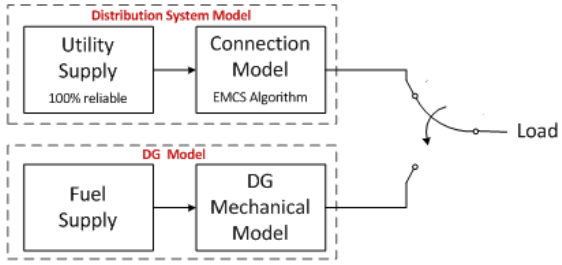


Fig. 5.2: DG and Distribution System Models [54]

To study the impact of adding DG on the reliability of the Microgrids, three main phases must be included in this research, DG reliability modeling, adequacy evaluation for the DG, and DG reliability integration.

5.3 DG Reliability Modeling

The DG reliability model consists of two models: the fuel supply model (i.e. availability of the fuel to supply the DG unit) and the mechanical model which represents the ability of the DG to operate successfully. There are two types of DG modeling, conventional DG modeling and renewable DG modeling.

5.3.1 Conventional DG

The conventional distributed generator in this research is used as a backup, where the fuel supply is 100% reliable. The mechanical model has two states: up state when the DG works successfully, and down state when the DG fails to work successfully, also, it is assumed that the conventional distributed generator has also full capacity output or zero capacity output, all these assumptions are shown in Fig. 5.3 below,

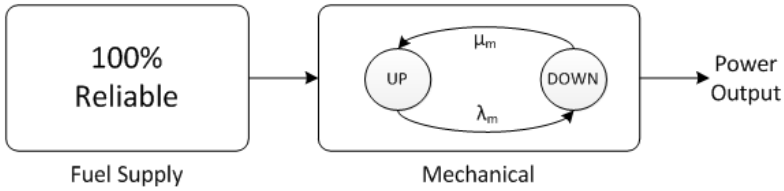


Fig. 5.3: Reliability Model for the Conventional Distributed Generation [54]

(λ_m) is the mechanical failure rate and it defined as the transition from the up state to the down state, (μ_m) is the mechanical repair rate and it defined as the transition from the down state to the up state. (A) and (U) for the conventional DG are show below [54],

$$A_{DG} = \frac{\mu_m}{\mu_m + \lambda_m} = \frac{MTTF_m}{MTTF_m + MTTR_m} \tag{5.1}$$

$$U_{DG} = \frac{\lambda_m}{\mu_m + \lambda_m} = \frac{MTTR_m}{MTTF_m + MTTR_m} \tag{5.2}$$

When the nominal output power for the conventional DG is equal to the available DG power (P_{DG}), then it is sure that the mechanical model is in the up state.

The power output probability for the conventional DG is shown in Table 5.1, called the capacity probability table (CPT).

Table 5.1: Capacity Probability Table [54]

State		Power Output	Probability
1	Up	P_{DG}	A_{DG}
0	Down	0	$1 - A_{DG}$

5.3.2 Renewable DG

The output power for the renewable DG is varying due to the availability of the input source, the renewable resources can be used as a backup DG if the output power is enough to supply the load demand during the interruption. If the load demand is more than the DG output power, then the DG is disconnected. In the renewable distributed generation, same as the conventional DG, the mechanical model will also has two states up and down, the (A) and (U) are given in (5.1) and (5.2).

In this research, the historical wind speed will be forecasted by ARMA, Markov, and Pdf models in order to get the forecasted wind power to be used in the wind DG. Wind power will be used to evaluate the impact of adding renewable DG on the Microgrids.

The historical per unit wind power for AL Dhahran KSA are shown in Fig. 5.4 below.

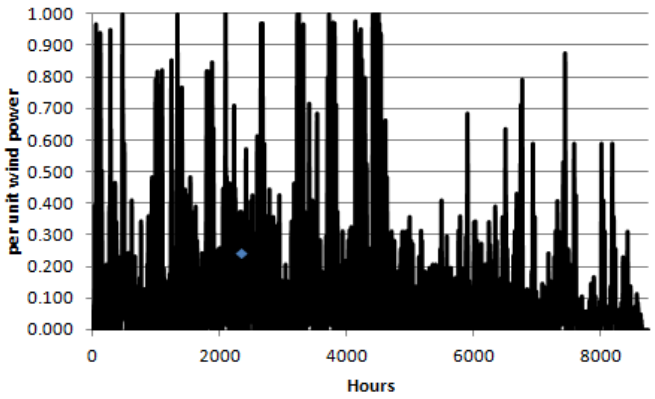


Fig. 5.4: Historical Per Unit Wind Power

To evaluate the adequacy for the renewable DG, the hourly per unit renewable power must be arranged in descending order. Then, number of segments will be defined (n), where (n+1) is the total number of levels. Depending on number of segments, the per unit power will be classified, as shown on Fig. 5.5 below

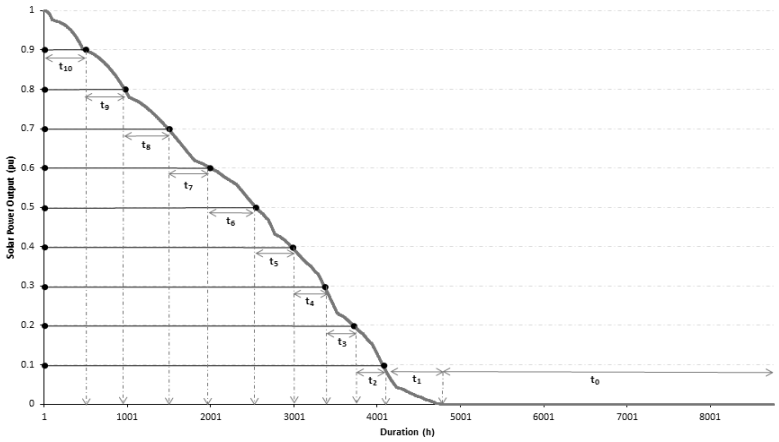


Fig. 5.5: Segments for Renewable Per Unit Power [54]

The CPT for the renewable DG for each segment is shown in table 5.2 below, where the probability depends on the availability of the input source, the output power will be zero either if the source is not available or if the mechanical model is in down state.

Table 5.2: Capacity Probability Table for the Renewable DG [54]

States		Power Output	Capacity Outage	Probability
0	Down	0	100%	$A_{DG}\frac{t_0}{D} + U_{DG}$
1	Up (Derated)	ΔP_{DG}	$100\left(1-\frac{1}{N}\right)\%$	$A_{DG}\frac{t_1}{D}$
N	Up	$N\Delta P_{DG}$	0%	$A_{DG}\frac{t_N}{D}$

Where N is the number of segments, t is the time per segment that the power falls in it, and D is the number of hours per year.

The steps for calculating the CPT for the renewable distributed generation are:

1. Arrange the hourly wind power output curve in descending order.
2. Define the power output levels as segments of the rated power.
3. For each segment, measure the total time that the power output falls within the segment.
4. Divide the total time of each segment by the total number of hours in one year to calculate the probability of each segment.
5. Using the probability of each segment and the mechanical availability of the unit, calculate the capacity probability for each level.

5.4 Adequacy Evaluation for the DG

5.4.1 Load Modeling

Three types of customers are considered in this study, industrial, residential, and commercial. Daily, weekly, and annual per unit load demand are shown in Fig. 5.6, 5.7, and 5.8 below [58, 59, and 60]. Where the demand probability table for the load can be

found in the same procedure of calculating the capacity probability table for the renewable DG, and it is called DPT.

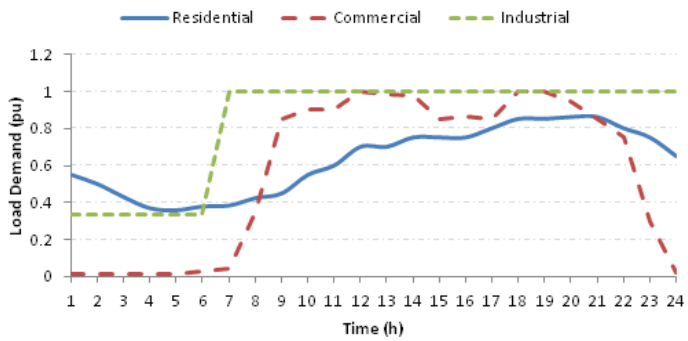


Fig. 5.6: Daily Load Demand

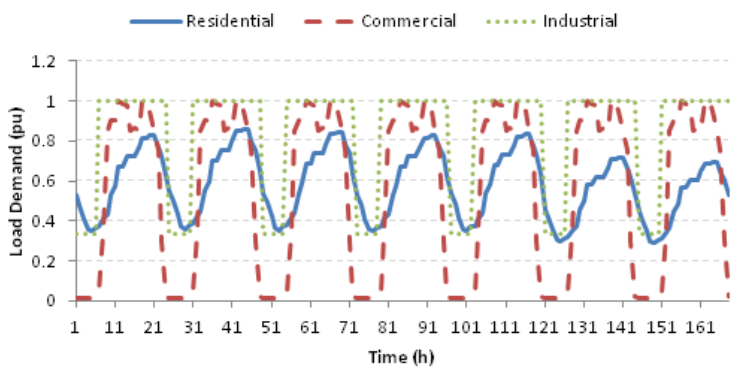


Fig. 5.7: Weekly Load Demand

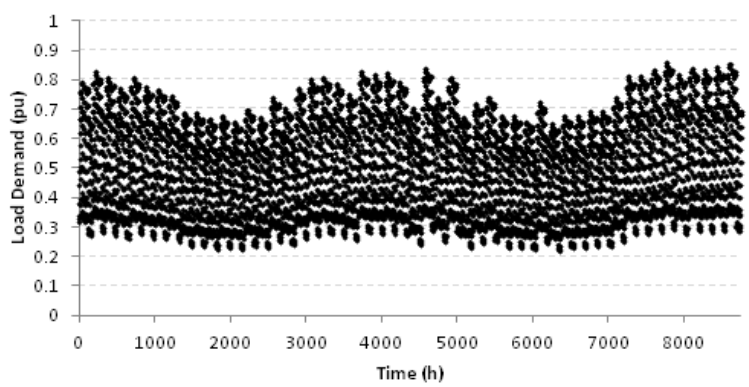


Fig. 5.8: Annual Load Demand for the Residential Customer

5.4.2 DG Adequacy Assessment

The core of the adequacy process is comparing the time varying output power for the DG with the load demand, if the DG output power more than the load demand during the outages, this will lead to improve the reliability of the microgrids. The reliability can be improved either by reducing the frequency of the outages, or by reducing the duration for these outages, or by both. Reliability indices SAIFI, and SAIDI are the two major indicators for the reliability improving.

As mentioned in the thesis organization, the wind speed will be modeled and forecasted by ARMA, Markov Chain, and Pdf, then the forecasted power will be calculated from these three methods. So, different types of the DG will be used in this research, original wind DG, ARMA wind DG, Markov wind DG, and Pdf wind DG. The per unit output power for these DGs and the per unit for the load demand are shown in Fig. 5.9, and Fig. 5.10 below.

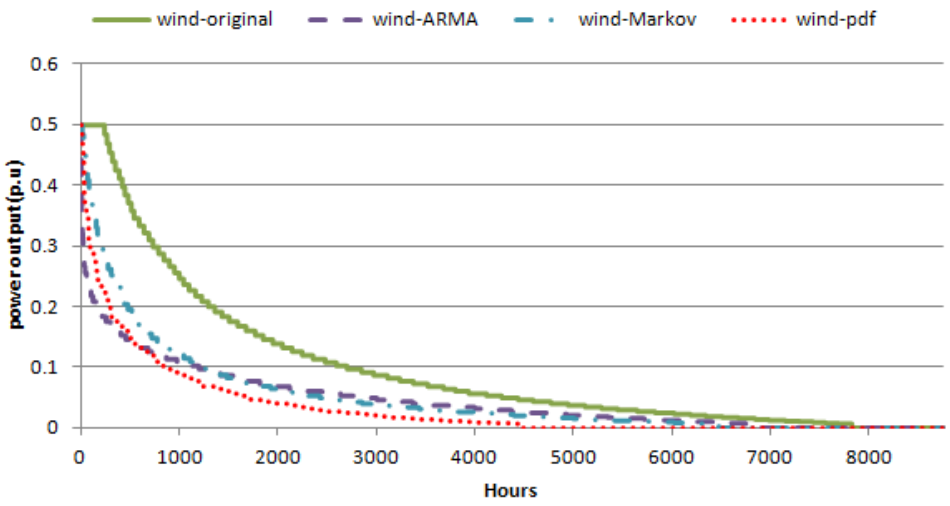


Fig.5.9: Per Unit Output Power for the DGs

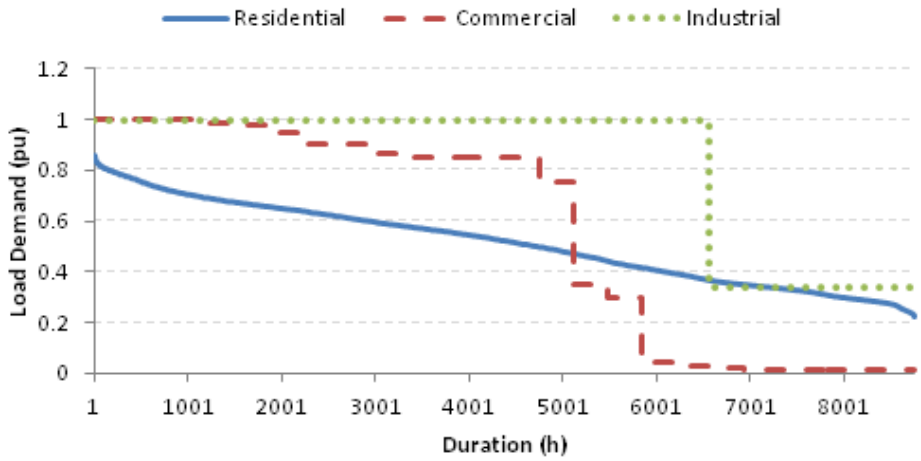


Fig. 5.10: Per Unit Load demand [54]

The loss of load probability is the major index to evaluate the adequacy and it indicates to the case where the generated DG power not enough to supply the load demand, where (LOLP) can be defined as below [54],

$$LOLP = P(Load > DG\ Capacity)$$

$$LOLP = \sum_{i=1}^{n} P_i \sum_{j=1}^{m} P(C_j < L_i) \tag{5.3}$$

n: is the number of levels in the demand probability table, m: is the number of levels in the capacity probability table, P_i is the load level probability, Cj is the level capacity for the DG.

To evaluate the adequacy for the DG, the steps can be summarized as below:

1- For both the DG and the load under study, the CPT and DPT are generated and the mean is computed for each segment to be used in the adequacy assessment.

2- For each DG power output segment in the CPT, the DPT is used to find the total time (or probability) for which the average load demand exceeds the average generated power for each segment.

3- The probability of each DG power output level is multiplied by the total time (or probability) found in step 2.

4- The cumulative sum of all the products in step 3 yields the LOLP.

An important definition is the RCR, which can be defined as the rated capacity ratio, and it can be expressed as below [54], where in this research, RCR for the wind is assumed to be 0.5.

$$RCR_{pu} = \frac{DG\ nameplate\ capacity}{Annual\ peak\ demand} \tag{5.4}$$

CPT for each segment in the DG, and DPT for each segment of the load are shown in table 5.3, and 5.4 below,

Table 5.3: CPT for Each Segment in the DG

State	Segment	Historical Wind DG			ARMA Wind DG			Markov Wind DG			Pdf Wind DG		
		Duration (h)	Average Output Power	Probability	Duration (h)	Average Output Power	Probability	Duration (h)	Average Output Power	Probability	Duration (h)	Average Output Power	Probability
0	0	928	0	0.1	1852	0	0.2	2279	0	0.3	4272	0	0.5
1	0.0 - 0.1	5129	0	0.6	5710	0	0.7	5248	0	0.6	3638	0	0.4
2	0.1 - 0.2	1345	0.1	0.2	1015	0.1	0.1	759	0.1	0.1	552	0.1	0.1
3	0.2 - 0.3	628	0.2	0.1	163	0.2	0	268	0.2	0	216	0.2	0
4	0.3 - 0.4	312	0.2	0	17	0.3	0	126	0.3	0	52	0.4	0
5	0.4 - 0.5	418	0.5	0	3	0.5	0	80	0.5	0	30	0.5	0
6	0.5 - 0.6	0	0	0	0	0	0	0	0	0	0	0	0
7	0.6 - 0.7	0	0	0	0	0	0	0	0	0	0	0	0
8	0.7 - 0.8	0	0	0	0	0	0	0	0	0	0	0	0
9	0.8 - 0.9	0	0	0	0	0	0	0	0	0	0	0	0
10	0.9 - 1	0	0	0	0	0	0	0	0	0	0	0	0

Table 5.4: DPT for Each Segment in the Load

State	Segment	Residential Customer			Commercial Customer			Industrial Customer		
		Duration (h)	Average Output Power	Probability	Duration (h)	Average Output Power	Probability	Duration (h)	Average Output Power	Probability
0	0	0	0.000	0.000	0	0.000	0.000	0	0.000	0.000
1	0.0 - 0.1	0	0.000	0.000	2920	0.017	0.333	0	0.000	0.000
2	0.1 - 0.2	0	0.000	0.000	0	0.000	0.000	0	0.000	0.000
3	0.2 - 0.3	837	0.276	0.096	365	0.300	0.042	0	0.000	0.000
4	0.3 - 0.4	1857	0.348	0.212	365	0.350	0.042	2190	0.337	0.250
5	0.4 - 0.5	1357	0.449	0.155	0	0.000	0.000	0	0.000	0.000
6	0.5 - 0.6	1793	0.553	0.205	0	0.000	0.000	0	0.000	0.000
7	0.6 - 0.7	1838	0.650	0.210	0	0.000	0.000	0	0.000	0.000
8	0.7 - 0.8	916	0.744	0.105	365	0.750	0.042	0	0.000	0.000
9	0.8 - 0.9	162	0.818	0.018	2555	0.866	0.292	0	0.000	0.000
10	0.9 - 1	0	0.000	0.000	2190	0.985	0.250	6570	1.000	0.750

Table 5.5 below shows the LOLP for the three customers with different types of DGs, and it's noted from this table that the lowest loss of load probability was when the historical wind distribution generator was installed to the commercial load, and the highest LOLP was when the ARMA wind distribution generator was installed to the industrial load.

Table 5.5: LOLP for the Three Customers

Customer	Historical Wind	ARMA Wind	Markov Wind	Pdf Wind
Residential	0.9745	0.9997	0.9944	0.9966
Commercial	0.6965	0.737	0.752	0.8284
Industrial	0.9792	0.9999	0.9941	0.9977

5.5 DG Reliability Integration

To evaluate the reliability of a networked distribution system including the DG, the DG and load models need to be integrated with the distribution system and its components. The load will receive the base load supply from the utility supply and the distribution connections. If the distribution system fails to supply the demand, the load will be disconnected from the distribution system and connected to the DG islanded system. The DG system model consists of the adequacy of the DG output power to supply the demand during the interruption, the DG mechanical operation, and the successful starting and switching the DG.

Successful DG starting and switching to disconnect the utility supply and connect the DG can be modeled as the probability to start and switch the DG when needed (P_{SS}) with a repair rate equal to (μ_{SS}). The starting and switching probability can be calculated as follows [54],

$$P_{ss} = \frac{Number\ of\ successful\ operations}{Total\ number\ of\ attempted\ operations} \tag{5.5}$$

When the DG is assumed to be 100% reliable and the probability to start and switch equal to one, the system can be modeled with the four states Markov model. Table 5.6 demonstrates the states and the status of each state.

Table 5.6: 4 States Markov Model System [54]

State		DG Adequacy	Main Supply	Load Status
1	11	1	1	U
2	01	0	1	U
3	10	1	0	U
4	00	0	0	D

To integrate the DG mechanical failure into the Markov model, the model is modified to include the DG failure states. As shown in Table 5.7, the system has 8 states and it is down when the distribution main supply and the DG adequacy state are down or when the main supply and the DG mechanical part are in a state of failure.

Table 5.7: 8 States Markov Model System [54]

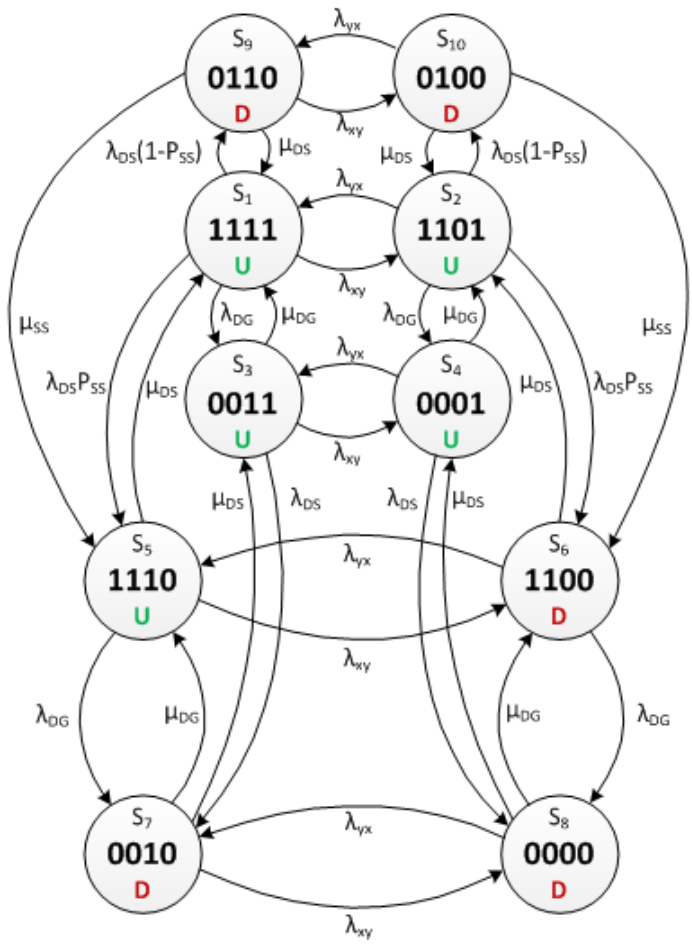
State		DG failure	DG Adequacy	Main Supply	Load Status
1	111	1	1	1	U
2	101	1	0	1	U
3	011	0	1	1	U
4	001	0	0	1	U
5	110	1	1	0	U
6	100	1	0	0	D
7	010	0	1	0	D
8	000	0	0	0	D

The last stage for the complete system model includes the probability of starting and switching the DG to the model as shown in Table 5.8. Some states in Table 5.8 (states 11–16) are considered unrealistic states and are removed from the state space.

Table 5.8: 16 States Markov Model System [54]

State		Starting/Switching	DG failure	DG Adequacy	Main Supply	Load Status
1	1111	1	1	1	1	U
2	1101	1	1	0	1	U
3	0011	0	0	1	1	U
4	0001	0	0	0	1	U
5	1110	1	1	1	0	U
6	1100	1	1	0	0	D
7	0010	0	0	1	0	D
8	0000	0	0	0	0	D
9	0110	0	1	1	0	D
10	0100	0	1	0	0	D
11	1011	1	0	1	1	X
12	1010	1	0	1	0	X
13	1001	1	0	0	1	X
14	1000	1	0	0	0	X
15	0111	0	1	1	1	X
16	0101	0	1	0	1	X

The STM and STD for the Markov model for the system are shown in Fig. 5.11 below,



$$\sigma = \begin{bmatrix} 0 & \lambda_{xy} & \lambda_{DG} & 0 & \lambda_{DS}P_{SS} & 0 & 0 & 0 & \lambda_{DS}(1-P_{SS}) & 0 \\ \lambda_{yx} & 0 & 0 & \lambda_{DG} & 0 & \lambda_{DS}P_{SS} & 0 & 0 & 0 & \lambda_{DS}(1-P_{SS}) \\ \mu_{DG} & 0 & 0 & \lambda_{xy} & 0 & 0 & \lambda_{DS} & 0 & 0 & 0 \\ 0 & \mu_{DG} & \lambda_{yx} & 0 & 0 & 0 & 0 & \lambda_{DS} & 0 & 0 \\ \mu_{DS} & 0 & 0 & 0 & 0 & \lambda_{xy} & \lambda_{DG} & 0 & 0 & 0 \\ 0 & \mu_{DS} & 0 & 0 & \lambda_{yx} & 0 & 0 & \lambda_{DG} & 0 & 0 \\ 0 & 0 & \mu_{DS} & 0 & \mu_{DG} & 0 & 0 & \lambda_{xy} & 0 & 0 \\ 0 & 0 & 0 & \mu_{DS} & 0 & \mu_{DG} & \lambda_{yx} & 0 & 0 & 0 \\ \mu_{DS} & 0 & 0 & 0 & \mu_{SS} & 0 & 0 & 0 & 0 & \lambda_{xy} \\ 0 & \mu_{DS} & 0 & 0 & 0 & \mu_{SS} & 0 & 0 & \lambda_{yx} & 0 \end{bmatrix}$$

Fig. 5.11: STM and STD for the System [54]

The failure rate (λ_{DS}) and the repair rate (μ_{DS}) are for each load in the analyzed system. While (λ_{xy}) is the transition from the work state where the generated DG power is greater than the load demand to the down state where the load demand is greater than the generated DG power, and the (λ_{yx}) is the transition from the down state to the work state, as shown in Fig. 5.12 below,

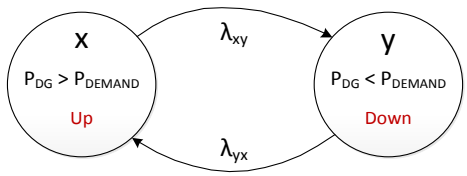


Fig. 5.12: States for DG's Adequacy [54]

$$\lambda_{xy}^{i} = \frac{Number\ of\ observed\ transitions\ from\ x\ to\ y}{Total\ time\ spent\ in\ x} = \frac{N_{xy}}{D_x} \tag{5.6}$$

Where (λ_{xy}^{i}) is calculated for each load demand level (i), then the total (λ_{xy}) is calculated as below equations [54], where (P_i) is the probability to stay in level (i).

$$\lambda_{xy} = \lambda_{xy}^{1} P_1 + \lambda_{xy}^{2} P_2 + \cdots + \lambda_{xy}^{n} P_n \tag{5.7}$$

$$\lambda_{xy} = \sum_{i=1}^{n} \lambda_{xy}^{i} P_i = \sum_{i=1}^{n} \frac{N_{xy}^{i}}{D_x^{i}} P_i. \tag{5.8}$$

Also the transition (λ_{yx}) can be calculated as follow,

$$\lambda_{yx} = \lambda_{yx}^{1} P_1 + \lambda_{yx}^{2} P_2 + \cdots + \lambda_{yx}^{n} P_n \tag{5.9}$$

$$\lambda_{yx} = \sum_{i=1}^{n} \lambda_{yx}^{i} P_i = \sum_{i=1}^{n} \frac{N_{yx}^{i}}{D_y^{i}} P_i. \tag{5.10}$$

5.6 RBTS Reliability Analysis Including DG

In this research, the Roy Billinton test system (RBTS) is used to evaluate the reliability under different scenarios. The RBTS has been referenced for many reliability studies and evaluation techniques in the literature. The advantage of the RBTS is the availability of the practical reliability data for all components. Another advantage is the manageable size of this system, which makes it easier to perform hand calculations to verify any reliability model or technique used to evaluate the reliability indices.

The RBTS has 5 loads busbars (Bus 2-Bus 6) with different connections and characteristics for each subsystem. The single line diagram for the RBTS system is shown in Fig. 5.13.

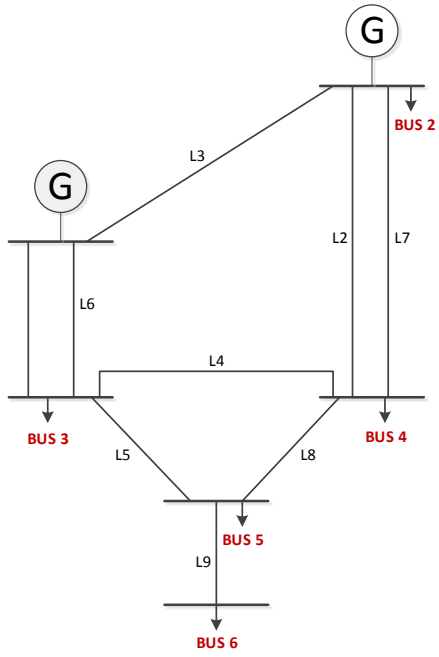


Fig. 5.13: Single Line Diagram for RBTS

The following comments are related to the RBTS under study in this research:

- All feeders and transformers are assumed to be equipped with interruption devices to isolate any sustained failure. It is assumed that all interruption devices in the system are 100% reliable (fuses, disconnects, and breakers) and capable of isolating the faulted segment instantaneously. The switching time is considered to be zero or less than 5 minutes where the event is considered as momentary interruption based on the IEEE standard 1366.
- The normally open tie switches are also considered 100% reliable with zero switching time.
- Transformers connected for residential, commercial, and governmental users are considered utility property. Therefore, the transformers are included in the single line diagrams and in the reliability evaluation. On the other hand, the small industrial customers are connected to the high voltage side, and the transformers in this case are customer property. These transformers are not shown in the single line diagram and not included in the calculation.
- The main feeders in the system can be either overhead lines or underground cables.
- It is assumed that adequate capacity is installed in the system for the normal operation and all failure scenarios. All the lines and components are within the capacity limits.
- The initial state of the test systems is assumed to be in normal operation mode, where all the components and lines in the system work properly.
- The average load given for each load point is the average load seen at each load point based on the average consumption over a year.

The Bus 4 of the RBTS, shown in Fig. 5.14, is used to evaluate the reliability of the microgrids, where the connection of the system is networked and the renewable DGs are integrated in the system. The reliability analysis of the microgrids consists of two stages, the networked connection analysis and the DG integration. The connection analysis is performed using the encoded Markov cut set (EMCS) method explained in [57].

Then, WTG is integrated to the system to see the impact of adding DG on the reliability of the Microgrids by finding several reliability indices like SAIFI, SAIDI, and ENS. The failure rate for the wind DG will be considered as 2 f/y, while the repair time will be considered as 48 h. In addition, for the DG P_{ss} is assumed 0.95, and the repair time 12h.

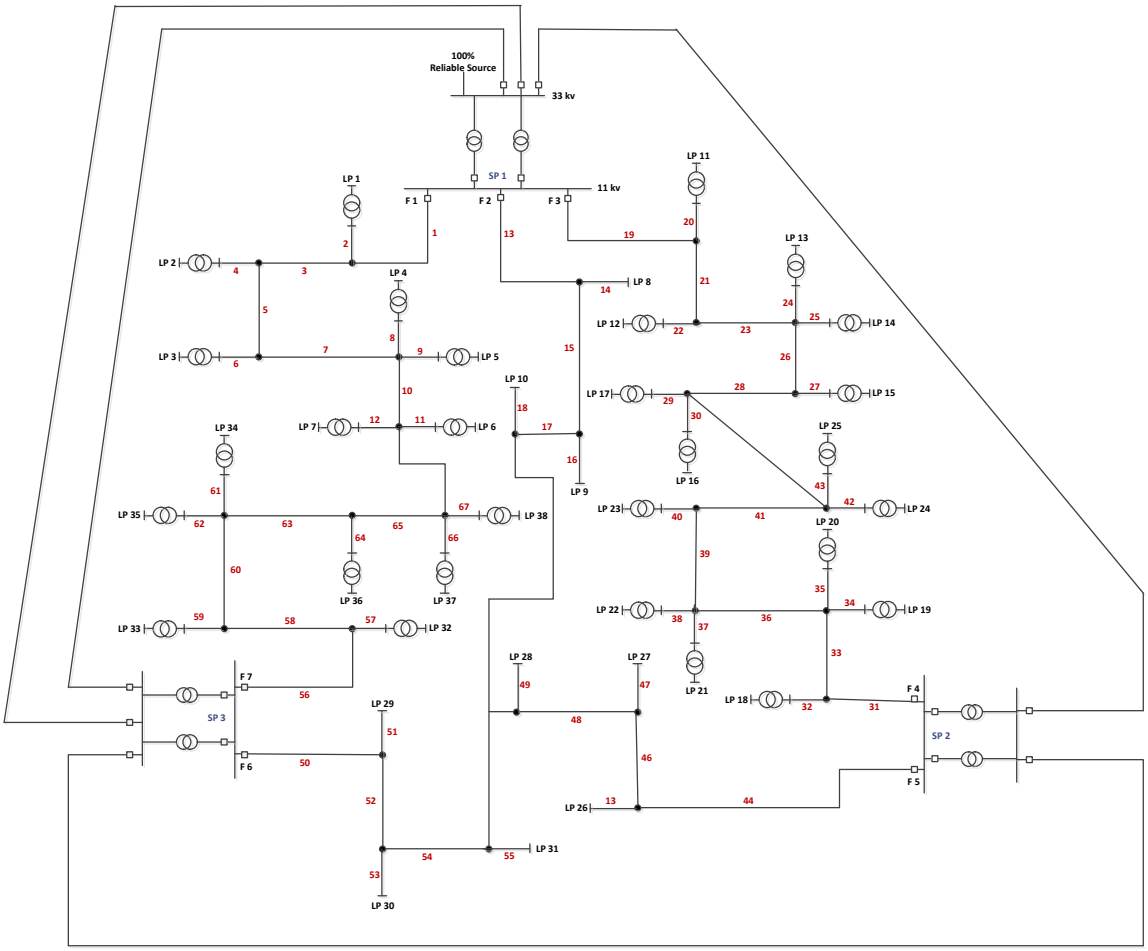


Fig. 5.14: 4 Bus RBTS [54]

The reliability data [57] for all the load points in the RBTS are shown below in table 5.9.

Table 5.9: Reliability Data for all the Load Points in RBTS

Load Points	Type	Average Load (MW)	Number of customers	A	U	MTT (y)	AIF (f/y)	AID (h/y)	FD (h/f)
1	Residential	0.545	220	0.999635	0.000365	18.5076	0.054	3.194	59.1431
2	Residential	0.545	220	0.99963	0.00037	15.6737	0.0638	3.2427	50.8511
3	Residential	0.545	220	0.999635	0.000365	18.4972	0.054	3.194	59.1091
4	Residential	0.545	220	0.999628	0.000372	14.9101	0.067	3.259	48.6148
5	Residential	0.5	200	0.99963	0.00037	15.6694	0.0638	3.2428	50.8361
6	Commercial	0.415	10	0.999628	0.000372	14.9099	0.067	3.259	48.6138
7	Commercial	0.415	10	0.99963	0.00037	15.6693	0.0638	3.2428	50.835
8	Industrial	1	1	0.999978	0.000022	25.6368	0.039	0.195	4.9997
9	Industrial	1.5	1	0.999972	0.000028	20.5108	0.0488	0.2438	4.9998
10	Industrial	1	1	0.99997	0.00003	19.231	0.052	0.26	5
11	Residential	0.545	220	0.999628	0.000372	14.9178	0.067	3.2589	48.6416
12	Residential	0.545	220	0.99963	0.00037	15.6745	0.0638	3.2427	50.854
13	Residential	0.545	220	0.99963	0.00037	15.6712	0.0638	3.2428	50.8428
14	Residential	0.5	200	0.999635	0.000365	18.4979	0.054	3.194	59.1114
15	Residential	0.5	200	0.99963	0.00037	15.6694	0.0638	3.2428	50.8362
16	Commercial	0.415	10	0.999635	0.000365	18.4947	0.054	3.1941	59.0997
17	Commercial	0.415	10	0.99963	0.00037	15.669	0.0638	3.2428	50.8343
18	Residential	0.545	220	0.99963	0.00037	15.6799	0.0638	3.2427	50.8645
19	Residential	0.545	220	0.999635	0.000365	18.5028	0.054	3.194	59.1214
20	Residential	0.545	220	0.99963	0.00037	15.6749	0.0638	3.2427	50.85
21	Residential	0.545	220	0.99963	0.00037	15.6715	0.0638	3.2428	50.8402
22	Residential	0.5	200	0.999635	0.000365	18.498	0.054	3.194	59.1079
23	Residential	0.5	200	0.99963	0.00037	15.6695	0.0638	3.2428	50.8351
24	Commercial	0.415	10	0.99963	0.00037	15.669	0.0638	3.2428	50.8343
25	Commercial	0.415	10	0.999635	0.000365	18.4947	0.054	3.1941	59.0997
26	Industrial	1	1	0.999972	0.000028	20.5108	0.0488	0.2438	4.9997
27	Industrial	1	1	0.99997	0.00003	19.2291	0.052	0.26	4.9998
28	Industrial	1	1	0.999978	0.000022	25.6412	0.039	0.195	5
29	Industrial	1	1	0.999978	0.000022	25.6374	0.039	0.195	4.9996
30	Industrial	1	1	0.999972	0.000028	20.5105	0.0488	0.2438	4.9997
31	Industrial	1.5	1	0.999978	0.000022	25.6412	0.039	0.195	5
32	Residential	0.545	220	0.999628	0.000372	14.92	0.067	3.2589	48.6417
33	Residential	0.545	220	0.999628	0.000372	14.9164	0.067	3.259	48.6314
34	Residential	0.545	220	0.999635	0.000365	18.4997	0.054	3.194	59.1127
35	Residential	0.545	220	0.999628	0.000372	14.9131	0.067	3.259	48.6218
36	Residential	0.5	200	0.999635	0.000365	18.4965	0.054	3.1941	59.1038
37	Residential	0.5	200	0.999628	0.000372	14.9099	0.067	3.259	48.6138
38	Commercial	0.415	10	0.999635	0.000365	18.4951	0.054	3.1941	59.1006

5.6.1 Load Reliability Indices Evaluation

Different case studies are discussed in this research. First, the WTG is integrated to the system where the different wind speed modeling methods (original wind, ARMA, Markov, and pdf) are considered. The WTG with different wind speed modeling techniques is connected to load point 1 (LP1) where the three types of customers (Residential, Commercial, and Industrial) are evaluated.

The AID, AIF, and the percentage change from the original historical wind speed for LP1 at Al Dhahran – KSA are calculated, as shown in Figs. 5.15, 5.16, and 5.17. In each figure, the impact of the wind speed and power is shown for each customer. In general, the ARMA model gives better reliability indices when it is compared with the Markov and pdf models. In these figures, the AID and AIF are shown for AL Dhahran to demonstrate the sensitivity of the modeling techniques to the wind speed data.

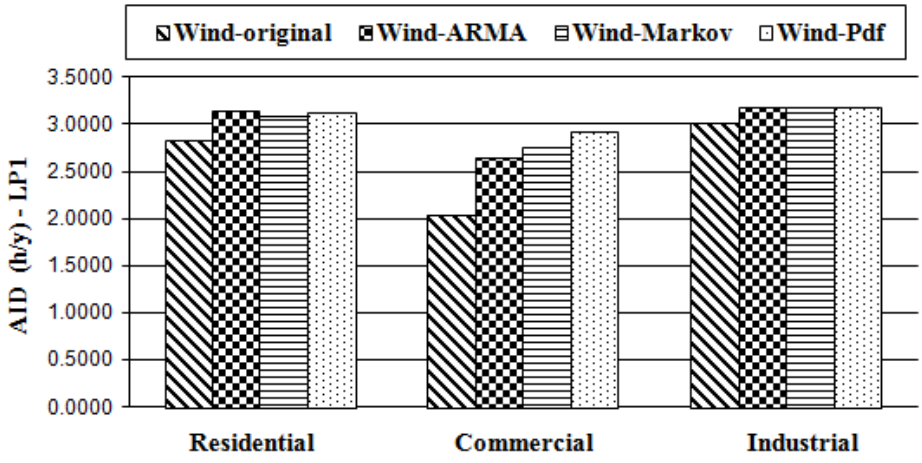


Fig. 5.15: AID for LP1 for Different Types of Customers

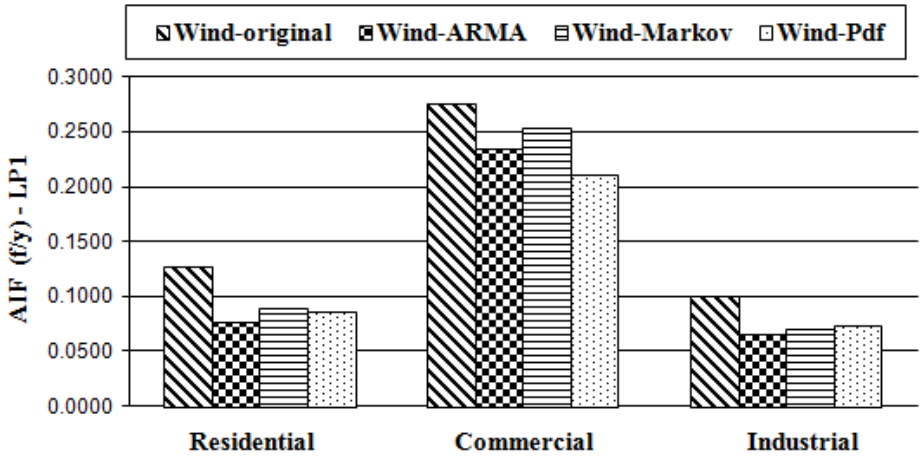


Fig. 5.16: AIF for LP1 for Different Types of Customers

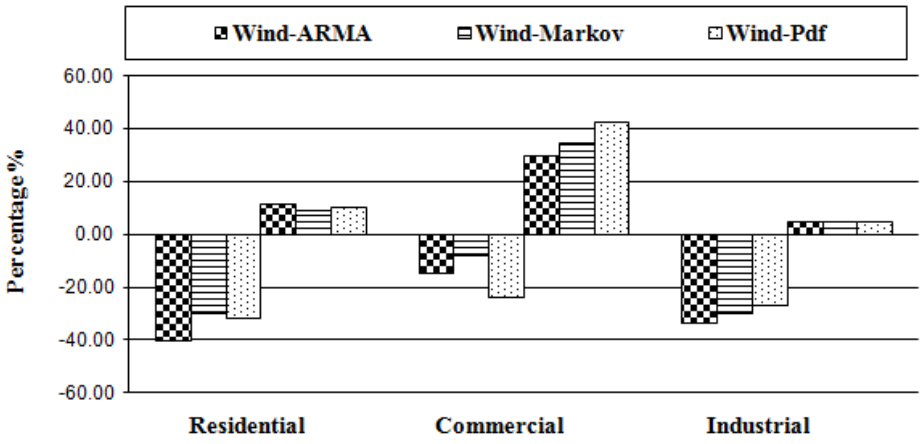


Fig. 5.17: Percentage Change from the Original Wind Speed

5.6.2 System Reliability Indices Evaluation

The second case is when the WTG with different wind speed and power modeling techniques is connected at each load point separately in the RBTS-Bus 4. Figs. 5.18, 5.19, and 5.20, demonstrate the impact of each load point type and each wind speed modeling technique on the system reliability indices, SAIFI, SAIDI, and ENS.

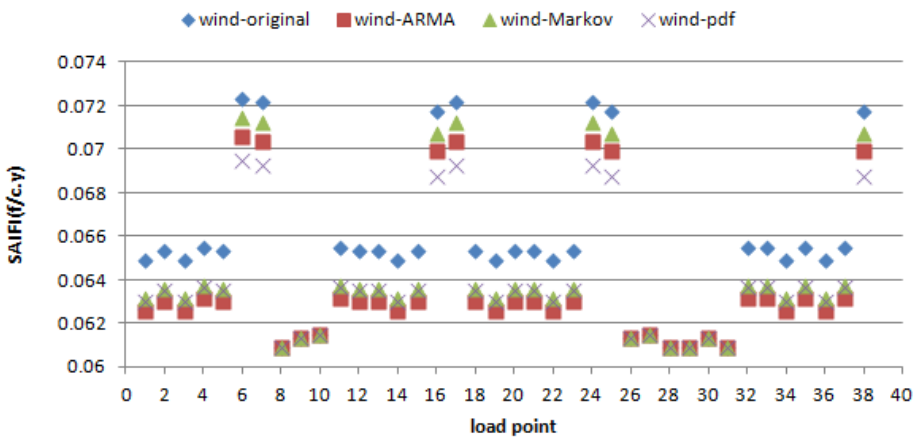


Fig. 5.18: SAIFI When WTG is Connected to Each Load Point

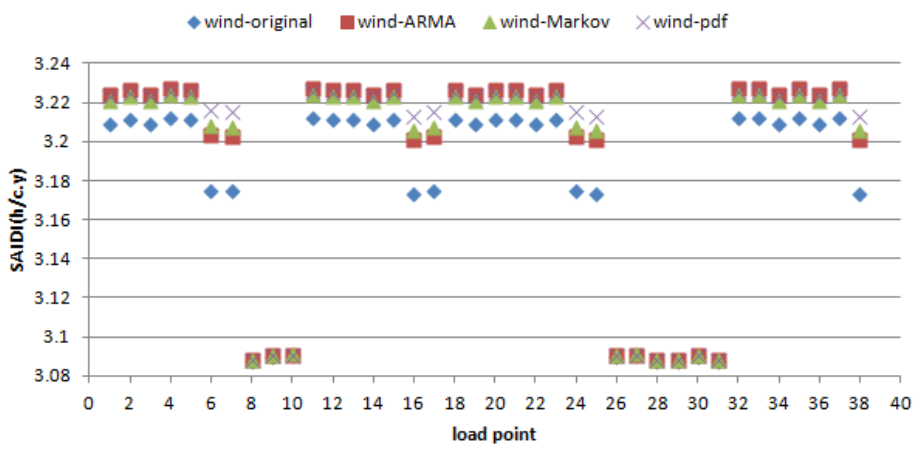


Fig. 5.19: SAIDI When WTG is Connected to Each Load Point

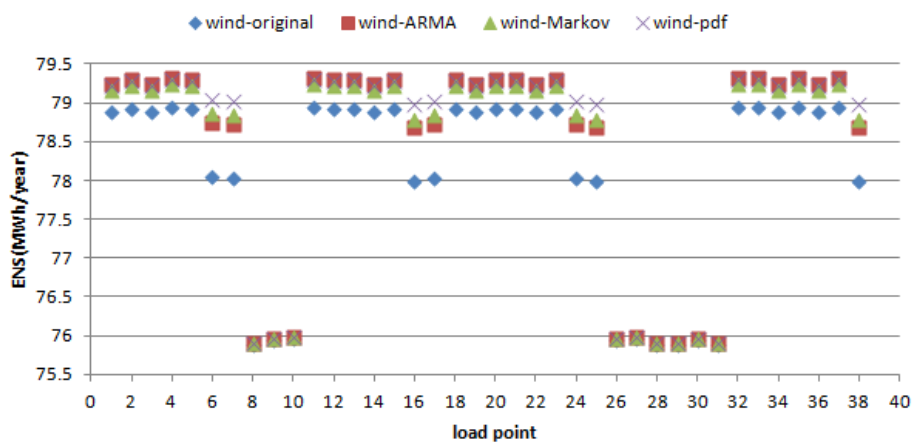


Fig. 5.20: ENS When WTG is Connected to Each Load Point

In this case, it's noted that ARMA wind generator has the lowest SAIFI and the highest SAIDI and ENS in the residential and industrial customers comparing with other types of wind generators.

5.7 Impact of Wind Speed Modeling on the Load and System Reliability Indices

The comparison will be done between the reliability results of this research for adding wind DGs with different modeling techniques to RBTS, with previous research results for M. Al-Muhaini, G.T. Heydt," Evaluating Future Power Distribution System Reliability Including Distributed Generation" [54].

In the load reliability evaluation, WTG with different modeling techniques was integrated to the LP1, the load reliability indices can be summarized as shown in table 5.10 below,

Table 5.10: Load Reliability Indices for LP1

	Residential		**Commercial**		**Industrial**	
DG	AID	AIF	AID	AIF	AID	AIF
Wind -ARMA	3.1472	0.0759	2.6483	0.2351	3.1688	0.0658
Wind - Markov	3.0792	0.0889	2.7464	0.2531	3.1719	0.0698
Wind -pdf	3.1260	0.0861	2.9125	0.2106	3.1694	0.0727

The results for the load reliability indices after adding wind generator without any modeling and forecasting process as Reference [54] technique, are shown in table 5.11,

Table 5.11: Load Reliability Indices for LP1 from Reference [54]

	Residential		**Commercial**		**Industrial**	
DG	AID	AIF	AID	AIF	AID	AIF
Wind	2.8246	0.1263	2.0409	0.2753	3.0189	0.0992

The percentage of change between both studies can be obtained from table 5.12 below,

Table 5.12: Percentage of Change Between Both Studies

	Residential		Commercial		Industrial	
	Percentage of change		Percentage of change		Percentage of change	
DG	AID	AIF	AID	AIF	AID	AIF
Wind -ARMA	11.4	-39.9	29.8	-14.6	4.96	-33.7
Wind - Markov	9.0	-29.6	34.6	-8.1	5.07	-29.6
Wind -pdf	10.7	-31.8	42.7	-23.5	4.98	-26.7

It's noted that ARMA WTG has the maximum difference in the AIF for the residential customer, and the minimum difference in the AID for the industrial customer. Where the minimum difference in the AIF was for the commercial customer with Markov WTG, and the maximum difference in the AID was for the commercial customer with Pdf WTG.

In the system reliability evaluation, WTG with different modeling techniques was integrated to the LP1, the system reliability indices can be summarized as shown in table 5.13 below,

Table 5.13: System Reliability Indices for LP1

	Residential		Commercial		Industrial	
DG	SAIDI	SAIFI	SAIDI	SAIFI	SAIDI	SAIFI
Wind -ARMA	3.223995	0.06256	3.2010	0.0699	3.2248	0.0621
Wind - Markov	3.220865	0.063158	3.2055	0.0707	3.2251	0.0623
Wind -pdf	3.223019	0.063029	3.2132	0.0688	3.225	0.0624

The results for the system reliability indices after adding wind generator without any modeling and forecasting process as Reference [54] technique, are shown in table 5.14 below,

Table 5.14: System Reliability Indices for LP1 from Reference [54]

	Residential		Commercial		Industrial	
DG	SAIDI	SAIFI	SAIDI	SAIFI	SAIDI	SAIFI
Wind	3.209	0.065	3.173	0.072	3.218	0.064

The percentage of change between both studies can be obtained from table 5.15 below,

Table 5.15: Percentage of Change Between Both Studies

	Residential		Commercial		Industrial	
	Percentage of change		Percentage of change		Percentage of change	
DG	AID	AIF	AID	AIF	AID	AIF
Wind -ARMA	0.46	-3.57	0.88	-2.51	0.208	-2.36
Wind - Markov	0.37	-2.65	1.02	-1.39	0.218	-2.04
Wind -pdf	0.43	-2.85	1.26	-4.04	0.214	-1.89

The maximum difference in the AIF was for the commercial customer with Pdf WTG, and it was in the negative order, and the minimum difference in the AIF was for the commercial customer with Markov WTG, and it was in the negative order.

Where the maximum difference in the AID was for the commercial customer with Pdf WTG, and it was in the positive order, and the minimum difference in the AID was for the industrial customer with ARMA WTG, and it was in the positive order.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In the first phase of this research, three wind speed modeling techniques were investigated, ARMA time series, Markov chains, and pdf models. The accurate modeling and forecasting wind speed and power will lead for improving the reliability by arranging a correct future planning and maintenance operations depending on the forecasted results. The main conclusions from this phase can be summarized as follow:

- More accurate long term wind speed data gives more accurate forecasted wind speed and power. Also, removing the outlier from the original data gives more chances for better forecasted results.

- It is difficult to identify the ARMA order by only analyzing the PACF and ACF, therefore, the AIC values are used to determine the best order for ARMA. Removing the outlier can reduce the number of lags included in the ARMA forecasting equation.

- Constructing the transition matrix for a large number of components or states is a complicated and time consuming task. On the other hand, higher number of states will give more accurate forecasted values.

- Pdf model is very sensitive to the distribution parameter values, where small changing in these values will lead to have forecasted data with distribution function not as the original distribution.

- In the wind power simulation, the accurate cut-in and cut-out values must be determined depending on the lowest and the highest wind speed values, which mean suitable wind turbine size must be installed depending on the wind speed range in each location.

- ARMA model was the best model for forecasting the wind speed and power comparing Markov and Pdf methods.

The second phase and the main objective of this research is to investigate the impact of the wind speed modeling techniques on the load and system reliability indices of electric microgrids.

The reliability analysis showed that the load and system reliability analysis are sensitive to the wind speed modeling techniques and ARMA model gives better reliability indices when it is compared with the Markov and pdf models. The sensitivity of the indices can also be affected by the historical wind speed data and type of customers in the system.

6.2 Future Work

This work can be extended to improve the area of assessing and evaluating the distribution system reliability, such as,

- Adding the energy storage model for the DG system in the reliability evaluation for the active distribution network.

- Finding the optimal DG's size and location that will have the highest reliability improvement.
- Study the reliability evaluation by integrating different types of DGs in the same network.

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