

**VOLTAGE SENSITIVITY-BASED DEMAND RESPONSE IN
DISTRIBUTION SYSTEMS**

BY

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MASTER OF SCIENCE

In

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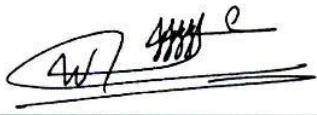
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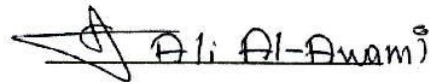
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The thesis is dedicated to my loving parents and family whose continuous support, guidance, and prayers helped me in many academic aspirations.

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LIST OF SYMBOLS

β_L	Status for The Minimum Temperature Limit
β_o	Status for The Intermediate Temperature
β_M	Status for The Maximum Temperature Limit
δ_i	Sensitivity of the node
ω	Output of the Input Layer for The Neural Network
θ_L	Lower Temperature Boundary
θ_U	Upper Temperature Boundary
φ	Transfer Function
P_{limit}	Reduced Power Limit
p_i	Instantaneous Power of The Node
$\Delta P_{threshold}$	Power Threshold
Δt	Time Instant
ΔT	Temperature Deadband
v_i	Voltage of the Node

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
DERMS	Distributed Energy Management Systems
DGs	Distributed Generation
DPL	DIgSILENT Programming Language
DR	Demand Response
DSM	Demand Side Management
DSOs	Distribution System Operators
EVs	Electric Vehicles
FCR-N	Frequency-Controlled Reserves for Normal
HVAC	Heating Ventilation and Air-Conditioning
IoT	Internet of Things
ML	Machine Learning
MLP	Multi-Layer Perceptron
NN	Neural Networks
PSO	Particle Swarm Optimization

RES	Renewable Energy Resources
SC	Shunt Capacitor
TCLs	Thermostatically Controlled Loads
V2G	Vehicle-to-Grid

THESIS ABSTRACT

NAME: Bilal Khan

TITLE OF STUDY: Voltage Sensitivity-Based Demand Response in Distribution Systems

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Advancement and innovations in technology, information, and smart grids have induced novel options in the control and management of power distribution systems. Traditional bulk grid services that were provided by power generation sides such as voltage regulation, supply-demand balancing, ancillary services, and contingency reserves are now partially supplied by demand resources. Enhanced system efficiency, reliability, and sustainability in terms of Renewable Energy Resources (RES) integration can be expected through Demand Response (DR) programs. Thermostatically Controlled Loads (TCLs) show great potential for demand-side management (DSM) in smart grids as a prominent DR resource. They can be aggregated and controlled autonomously, i.e. without the need for communication.

A Space Heating (SH) load is a typical TCLs with a heat-storing capability that is

a great DR resource —a fast response option at a low cost. Load management of the distribution system’s peak demand will defer investments in new generation and infrastructure capacity up-gradations. Due to these benefits DR has attained significant attention in the smart technology era as an economical solution. An autonomous DR control scheme is proposed to alleviate voltage violations of the local distribution system by managing SH loads. The proposed DR framework can be easily extended for air conditioning loads (AC) with little modifications. The proposed scheme attempts to set the SH operating point intelligently based on local measurements only. The scheme bases its decisions on the voltage at the premise (measured locally) and the premise’s voltage-to-power sensitivity (which is estimated using local measurements only). The proposed work introduces a new source of system-level flexibility, through thermostatic demands reduction with the load voltage sensitivity-based autonomous approach. By deploying machine learning, the proposed control scheme ensures that multiple SH loads, located at different nodes on the distribution system, contribute in a fair manner to mitigate voltage violations of the system without the need for communication. This controller also ensures an acceptable comfort level for the end-users. Simulation results verify the efficacy of the proposed control scheme in revamping voltage profile while maintaining fairness among and comfort of end-users.

ملخص الرسالة

الاسم: بلال خان

عنوان الدراسة: تأثير حساسية الجهد على أساس استجابة الطلب في أنظمة التوزيع

التخصص: قسم الهندسة الكهربائية

تاريخ الدرجة العلمية: 28 أبريل 2020

أدى التقدم والابتكارات في مجال التكنولوجيا والمعلومات والشبكات الذكية إلى ظهور خيارات جديدة في التحكم في أنظمة توزيع الطاقة وإدارتها. يتم توفير خدمات الشبكة الكليّة التقليدية، التي تم توفيرها من قبل جهات توليد الطاقة، مثل تنظيم الجهد، وموازنة العرض والطلب، والخدمات المساعدة، واحتياطات الطوارئ من موارد الطلب بشكل جزئي. يمكن توقع كفاءة النظام المحسنة، والموثوقية، والاستدامة من حيث تكامل مصادر الطاقة المتجددة (RES) من خلال برامج الاستجابة للطلب (DR) تُظهر الأحمال التي يتم التحكم فيها حراريًا (TCLs) إمكانيات كبيرة لإدارة جانب الطلب (DSM) في الشبكات الذكية كمورد DR بارز. يمكن تجميعها والتحكم فيها بشكل مستقل، أي دون الحاجة إلى التواصل.

حمل المدفأة (SH) هو نموذج TCL عادي مع إمكانية تخزين الحرارة وهو مورد DR رائع - خيار استجابة سريع بتكلفة منخفضة. ستؤدي إدارة الأحمال في ذروة الطلب في نظام التوزيع إلى تأجيل الاستثمارات في الجيل الجديد وتحسينات سعة البنية التحتية. نظرًا لهذه الفوائد، حظيت DR باهتمام كبير في عصر التكنولوجيا الذكية كحل اقتصادي. يُقترح مخطط تحكم DR مستقل لتخفيف انتهاكات الجهد لنظام التوزيع المحلي من خلال إدارة أحمال SH. يحاول المخطط المقترح ضبط نقطة تشغيل SH بذكاء بناءً على القياسات المحلية فقط. يعتمد المخطط في قراراته على الجهد في حدود العمل (يقاس محليًا) وحساسية الجهد إلى الطاقة في حدود العمل (والتي يتم تقديرها باستخدام القياسات المحلية فقط). يقدم العمل المقترح مصدرًا جديدًا للمرونة على مستوى النظام، من خلال تقليل الطلبات الحرارية مع الطريقة المستقلة القائمة على حساسية

الجهد. من خلال استخدام الذكاء الصناعي ، يضمن مخطط التحكم المقترح أن تساهم أحمال SH المتعددة ، الموجودة في نقاط مختلفة في نظام التوزيع ، بطريقة عادلة في التخفيف من انتهاكات الجهد للنظام دون الحاجة إلى الاتصال. كما تضمن وحدة التحكم هذه مستوى راحة مقبول للمستخدمين النهائيين. نتائج المحاكاة تظهر فعالية مخطط التحكم المقترح في تجديد ملامح الجهد مع الحفاظ على الإنصاف والراحة بين المستخدمين النهائيين.

CHAPTER 1

INTRODUCTION

Trends in power systems of the modern age are shifted towards energy security, and reductions in carbon footprint, by investing in renewables and distributed energy resources. Also, energy-efficient programs are implemented for decreasing, cost, renewable variability, DGs' (Distributed Generations) adverse effect on voltage, operation of inefficient peaking power plants, and carbon footprints. Recently Demand Side Management (DSM) programs can be utilized for several benefits, apart from to, peak shaving, i.e., reducing peak demands, reducing operation times of peaking units, deferring investments in the transmission and distribution infrastructure. Economic reductions of consumer consumption profiles improve the overall efficiency of aging infrastructures. High demands, results in the volatility of demand charges in vertical integrated or deregulated electricity markets. DR programs including DSM, are emerging solutions to many challenges in the operation of power systems. Demand response can be implemented in several ways, as a diverse range of activities are covered in the domain of DSM, such as load management and energy efficiency. Priced based programs are implemented, where, changes in electricity consumption are obtained in

response to variations in price. They are further categorized as a time of use rates, real-time pricing, and severe peak pricing programs.

DR is different from the generation counterparts in various aspects and this poses regulatory and technical barriers to the successful integration of DRs if left unattended. DR resources are quick in variation that is changing the consumption profile. Due to the ramp-up limitations, central generation power plants cannot change abruptly the power output correspondingly when required. Flexibility unavailability, which is the power system's ability in responding to the changes in stochastic supply and demands, is a major obstacle to increasing the shares of RES. DR resources, on the other hand, are faster in action to the power grid requirements since they can have larger ramp rates. However, in some cases, DSM resources are operated as a lumped response, not as flat as the continuous and smooth response of some generators. Also, load characteristics may not be well known from their operational perspective and thus, sometimes building their analytical models, to capture their diverse dynamic nature, is not trivial. Importantly, DR resources' operational constraints may be complicated when compared to centralized generators. For instance, in an ideal case, the shift and adjustment of loads should not variate energy service, like space heating for maintaining indoor user-specified range. In this situation, the DR resources are limited in application, and customers kept temperature limits/preferences that must be taken care of. Also, when many small demands such as TCLs are aggregated to offer grid services, modeling and controlling them becomes challenging. The main objective of DSM is to pro-actively engage end-users in allowing them to modify their consumption patterns when called by the grid operators while satisfying users' comfort

constraints.

1.1 Background

Increased environmental concerns arise tighter legislation such as climate change acts that set global temperature targets with a recognition for deep cuts in carbon emissions [3], [4]. These agreements set long-term strategies to address climate change by encouraging a low-carbon economy through unified emission targets. Reducing the impacts of power generation on climate and environment, demand reduction, phasing out fossil fuel-based generations and thus, a fast transitioning to RES is obvious. However, large-scale integration of Variable Renewable Energy (VRE) at such a pace will introduce social and technical challenges that need to be addressed for ensuring safe and reliable network operation e.g., thermal power plants will be operated in fast ramp-up and ramp-down rates for minimizing power curtailment from RES during high wind speeds and solar irradiance.

In the present technical advancement era load curtailments are possible through novel algorithms such as DSM and DR. These options help make power distribution system operation stress free, with additional perks for system operators, utility price reductions, infrastructure expansion deferrals and integration of RES. Also, its termed as Deployable DERS [5] i.e., ESS and DR may deliver high network capacity values than even that of solar PVs. Since important judging criteria regarding DR is as follows:

- DR can be deployed in areas where the existing network requires expansion due

to the load growth or outdated infrastructure, i.e., power system assets scheduled for replacement.

- In order to relieve network congestions, DR resources are able to reduce net power withdrawals or power injections.
- Continuous supply of services for the time period of network enhancements deferral.

DSM has been widely deployed since the early 1980s' however, the term DR has been introduced recently via the smart grid idea. Since then, DR programs have received attention from the policymakers and utility companies. DR has significant potential for avoiding costs associated with running outdated power plants that are mainly fossil fuel-based and help smoothen the transition to renewable generations [6]. However, there are some gaps that need to be addressed to fully attain the possible benefits from DR and DSM programs. DR is a customer behavior-based control decision targeting peak and energy bill reductions. DR offers flexibility to the customer in terms of what loads to be included in the DR and the period of curtailment. DSM is different than DR in terms of the controlling strategy and authority as DSM requires the customer's initial consent. DSM can be deployed through different load reduction options. Dr is categorized as: emergency DR, economic DR, and DR for ancillary services. Emergency DR is deployed to mitigate involuntary service interruptions at times of low generation. Economic DR allows electricity customers to participate in load reduction in exchange for incentives. The incentives, though, are expected to be more beneficial than productivity loss or convenience sacrifice. Ancillary service DR

ensures reliable and secure power grid operation due to their fast action.

LV distribution networks, during nominal operation, undergo extensive variations in load resulting in adverse effects on voltage profile. The demand response controller must be robust enough to address this issue, by improving the locality's voltage profile. Distribution networks are also subjected to configuration either due to expansion planning in the network resulting from increased customer demands or upgradations by the utility. However, re-configurations in the system also result from the daily operation of the distribution grid or during any contingencies e.g., line flow limitations, such as outage in some lines or feeders. Changes in system topology pose difficulties for the decentralized controllers, since the controller parameters rely on large quantity of system data. If the controller is not robust enough, any changes in the system topology will result in sub-optimal performance.

1.2 Research Motivation

DR resources can deliver numerous services to the power systems in general and distribution systems specifically. These services range from peak demand reductions, overload management, emergency backup assistance, and ancillary services provision at low cost since DR is allowing active consumer involvement in the frequency balancing work i.e., generation/demand balancing thus, adding flexibility [7]. DR's beneficial service provisions are further extended to increased time spans. Public sectors and governments, new policies help the new plans of renewable resources both dispatchable and non-dispatchable RES. However, the nature of renewables is variable which im-

pedes their integration in the existing grid. Due to variable RES integrations, power systems are experiencing a fast-paced revolution and DRs will serve a phenomenal purpose in helping achieve a 100% fully renewable grid. Since DR and DSM depend on selected changes to the consumption of end-user users without altering their comforts and incentives maybe offered greater in value than the discomfort. DR has received wide appreciation and acceptance for adding positive value to market efficiency and power systems reliability.

Bulk large scale power systems are one of the complex systems that consist of vast components and central operating generators. To regulate frequency within the normal operating range power demand balance is vital in the large interconnected system. All the earlier paradigm benefits and ancillary services can now be procured locally with DRs and cheaper as compared to the expensive reserves. Thus, rather than depending on fossil fuel-based generation resources to balance out demand-supply differences cheaper and greener alternatives can be tapped much faster for meeting the same objectives. Also, incremental value and deployment have been possible due to the emergence of smart grid technologies such as that of smart meters. DRs potential is now fully investigated on large scale, making DR further valuable in improving the reliability and efficiency of the power distribution systems [1].

1.2.1 Peak Demand Reducton

DR offers end users an opportunity to play an important role in the power systems operation. By minimizing or altering the consumption patterns during high demand periods responding to time-dependent rates or other financial incentives. Significant

financial savings and reliability provisions can be obtained through DR either to Distribution System Operators (DSOs) or residential DR aggregators. Due to the non-linear characteristics of the power systems losses are significantly higher during heavy loading where less efficient units may have to be operated. Thus, it's less efficient to operate systems with high demand characteristics. More notably, huge investments are spent on meeting this peak power demand.

To keep generation and demand balanced, bulk centralized power stations are dispatched and need to be installed further if there is a deficit in such large-scale generations. Additionally, significant reserve services are kept running and such idle generation is costly. Since if the load is not participated in balancing or ancillary service, the expensive generation following load prevails. Also, expensive reserve services must be procured to accommodate peak demands. Enabling DR resources during peak hours yield immense benefits at low cost avoiding or minimizing communication dependency.

1.2.2 Distribution Systems Congestion Management

A common problem in power systems is that of Congestion management. It becomes more prominent in competitive markets and deregulated markets. In order to meet the expanding power demands or deal with the rise in unplanned power trading, power distribution lines are often loaded close to and sometimes even above their nominal thermal ratings. Uncontrolled power flows may result in overloading and this phenomenon is termed as congestion. The radial architecture of the distribution systems makes congestion management difficult. As there is limited or no alternative

to re-route power. Also, the distribution networks' load resources are varying and diverse in nature and there is a lack of coincidence in line overloading's and peak demand hours. Thus, estimating the proper capacity and size of the distribution lines is difficult in the early network planning. If congestion management is not adequately handled it may lead to load interruptions given that the distribution systems serve as load centers.

An optimal DR strategy will avoid all the intricacies involved and obtain the benefits for the residential community in terms of voltage improvements, introduce diversity, offer incentives, and avoid incurred costs in congestion management by the DSOs. In order to coordinate such actions from many load aggregated resources, the concept of local market can be presented. Each load aggregator willing to take part in the market can submit a bidding curve which is an indication of their cost for overload management in the distribution systems. All bids will then be prioritized and evaluated in their congestion relief effectiveness in the distribution system. Multiple objectives can be framed in establishing such a local market structure. As the involvement in such services is cost-based and disputes may be eliminated relative to load curtailment traditional schemes.

1.2.3 Ancillary Service

Services in addition to routine operational tasks that are necessary to support the reliable energy transfer to loads are termed as ancillary services (AS). AS serve as added extra power to keep the load and generation balance in case sudden outage of a unit, higher demand than expected or forecasted, or if any other emergency arises.

AS are further categorized by their time zone characteristics as shown in Fig. 1.1, response duration and full response time, and usage pattern, i.e., how often they are called in action [8], [9]. AS markets differ significantly across regions and often contains a “regulation” part requiring a short span adaptations to the load in a real-time interval, one or more “spinning” service entities requiring to offer at short notices (from seconds to minutes) during a disturbance, and some “non-spinning” units or service requiring longer lead time responses around 30 minutes. During a disturbance of power system contingency, fast-acting service will be utilized first that supports the system frequency towards normal.

The generation side provided a load balancing service for two reasons. First, the market and regulation barriers hampered successful penetration of DR in the markets for ancillary services. Second, DR resources failed to meet the required objectives upon calling during their early development phase due to limited embedded control technology availability. Without an effective control strategy DR resources may face challenges in precisely tracking deployment instructions due to the load uncertainty or changes in the layout of the distribution systems.

Noteworthy aspect of controllable loads such as TCLs are their adequacy and ideal size, when aggregated, for providing reliability services [10]. Thus, improved reliability service, eliminating price volatility and reducing market inefficiency when DR resources are integrated with AS markets. Due to the increasing importance of DRs, new control strategies have been adopted for improving DR application, either through standalone or when aggregated in large-scale [11]. Flexibility provision from DRs can be faster than the governor’s actions of centralized generators which can

further enhance power systems reliability. DRs can be adopted for smoothing power fluctuations by regulating its inclusive functionality.

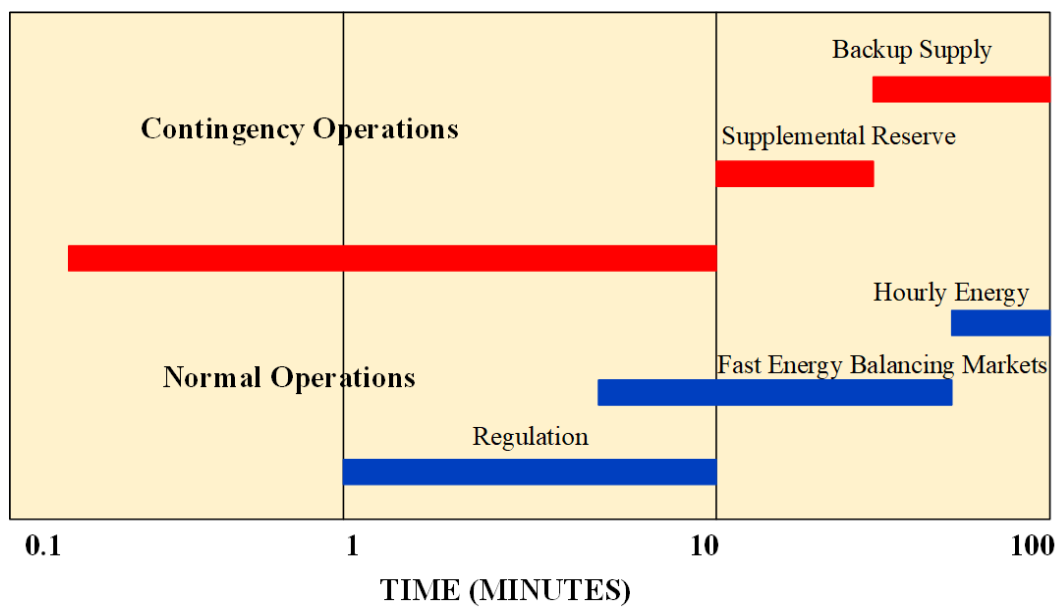


Figure 1.1: Ancilliary services categories of various resources [1].

1.2.4 Blackouts and DR's Response to Emergency

Large scale deployments and spanning wide regions, power systems have evolved in intricate non-linear systems that are vulnerable to blackouts. Though day-to-day life, health, and the socio-economic outlook is much dependent on them and large-scale blackouts may disrupt much of life's activities. For example, the blackouts of 1996 and 2003 in US incurred an estimated cost of 6 billion dollars financially [12], [13]. DSM resources have successfully managed peak demand crises around the world, where DR aggregators have a significant presence. As DSM programs are attracting attention they can be of tremendous importance in the absence or scarcity of other prevention resources to mitigate or eliminate blackouts. In the past, DR resources were procured directly when required during an emergency or cascading failure. During high power systems stresses insecurity is expected, thus, DRs can be employed by the operator's discretion. In return, compensation is made for the capacity that DRs provided during an emergency.

There is an opportunity to develop innovative ideas for more effective strategies for the prevention of blackouts. With increasing implementation of Advanced Metering Infrastructure (AMI), Distribution System Operators (DSOs) can significantly enhance load curtailments precision as AMIs provide more granularity in the control actions. Load resources such as TCLs and EVs can be aggregated to mitigate uncertainties in the action and control of single loads. When load aggregation resources meet a specific size requirement, it can be included and monitored online in

the Distributed Energy Management Systems (DERMS). Load aggregation increases the potential reward through expanded DR participation while eliminating comfort inconvenience risk to the participating end-users

1.2.5 Transactive Control with Continuous Response

DR resources can constantly respond to system interruptions or imbalances by a bi-directional approach termed as transactive by researchers at Pacific Northwest National Laboratory (PNNL). This outlines the paradigm shift in the way the power system used to be operated. Such a transactive approach provides coordination and control for active end-user's engagement and third-party flexibility service providers in a transparent and competitive manner. This is opposite to the event-based DSM, transactive response allows a continuous and precise change in power consumption. As per GridWise, transactive energy process it is a set of affordable and control strategy that allow the dynamic balance of generation and demands across the entire electrical network using value as an important operational parameter. Value basically refers to economic and market-based standard energy values.

Transactive energy encourages an autonomous environment for energy nodes that are distributed contrary to the traditional grid architecture. From the design perspective, the notable element is a transactive node in transactive energy, which is a node that makes automated actions embedded with a communicating agent. Such nodes submit bids first while considering operational constraints for its schedule.

1.2.6 Aiding the Integration of DGs

Variable renewable resources like wind and PV cause supply and demand imbalances due to their output variability which pose challenges for power system operators. Solving the issues of variation that cause voltage and frequency fluctuations, require more reserves and balancing services [14], [15]. Solutions are sought worldwide for RES integrations with the grid, and different standards are introduced. IEEE 1547 standards and its updated version IEEE 1547:2018 offer guidelines for the integration process. Since these standards are defined in general and they are not technology-specific nor it defines the exact method for its implementation, optimal solutions are yet to be figured out. These standards showcase best practices for using any technology with industrial preferred suitable procedures that will help the grid operators. They also allow interoperability to be in accord and avoid any issues that impact the stability and smoother operation of DGs integrated with the grid. Given the volatility and expansion of residential demands, the distribution network infrastructure changes, posing challenges for a decentralized demand response controller. Artificial Intelligence (AI) is widely used for highly complex and non-linear networks behavior learning. Introducing AI in demand response helps in successful DR implementation and achieves impressive results even during network reconfiguration or Distributed Generation (DGs) integration.

1.3 Thesis Objective

Centralized and decentralized control strategies are already implemented in the literature that require some extent of communication infrastructure to ensure successful demand side management. However, there are limitations inherent in existing communication-based designs, noteworthy are their slow response and high-price tags. Objective of the proposed DR controller is to use local voltage and sensitivity signals for attaining specific curtailment decisions based on the distribution system requirements. Decentralized and centralized autonomous controllers are already proposed but they are not robust to system reconfiguration and may ward off some key DR benefits, e.g., fairness. The objective of this thesis is to formulate an adaptive DR controller that will improve distribution system operation, revamp voltage profile, and achieve fairness. The objectives that will be addressed in this thesis are:

- To design a voltage sensitivities-based DR controller.
- To study the DR controller performance in-terms of system voltage profile improvement for various loading conditions, i.e., light and heavy.
- To evaluate the performance of the DR controller with Shunt Capacitor (SC), RES penetration such as wind, and system reconfiguration.
- To evaluate the performance of the DR controller in-terms of voltage profile improvement and customer comfort.

1.4 Thesis Methodology

To conduct the research of this thesis the following methodology and procedures will be carried out for the DR controller simulation:

- 1) DIgSILENT Powerfactory (Digital Electrical Network Simulation), a leading integrated power system analysis software will be used for simulating the proposed test system.
- 2) The sensitivity analysis of the test system will be performed.
 - a) for the normal system and b) for various system reconfigurations.
- 3) Evaluating the system DR requirements in-terms of voltage improvements, system loading condition, and distribution feeder congestion.
- 4) Designing a DR controller for the system satisfying various performance and robustness constraints.
- 5) Evaluating the proposed controller for different loading conditions and distribution network reconfiguration.

1.4.1 Main tasks

- Study the implemented work and advancements related to Demand Response programs.

Model Development and testing in DIgSILENT Powerfactory

- Develop the test distribution power system in DIgSILENT Powerfactory software.

- Learning the basics of DIgSILENT Programming Language (DPL).

Designing voltage sensitivity-based controller

- Writing codes to measure nodal voltages, estimate sensitivity, and update loads.
- Designing the ML-based DR controller based on nodal voltage and sensitivity.

Reconfiguring the distribution system

- Testing the proposed controller considering light and heavy loading conditions.
- Analyzing the proposed DR charge controller by changing the network topology.

Incorporating Wind Distributed Generation and Shunt Capacitor

- Including a DG unit to assess the effectiveness of the proposed methodology.
- Integrating shunt capacitor and on-load tap changing transformer in a system.

Investigating the proposed strategy's efficacy

- Evaluating the proposed controller's approach under various operating conditions in the distribution system.

1.5 Thesis Organization

The overall layout of the thesis is as such: Chapter 2 highlights related research gaps. It also covers various DSM and DR researches falling in the area of centralized, decentralized and autonomous controllers. Chapter 3 describes the proposed control

strategy, TCL model, and Machine Learning (ML)-based training. It also presents the concept of online sensitivity estimation. Chapter 4 elaborates the test distribution system used in this thesis work. Results and discussion are provided in Chapter 5. The thesis is concluded in Chapter 6.

CHAPTER 2

LITERATURE SURVEY

Increasing electric appliances and their constant grid connectivity through the Internet of Things (IoT) concept in smart grid present new challenges to the power grid. To ensure the power grid's stability, power supply and demand must be kept balanced in real-time. Maintaining the balance grows in complexity each day due to the load growth. Traditional solutions for peak demands and balancing services call upon peaking power plants that are less efficient and fossil-fueled. Environmental protection consciousness regarding carbon emissions proliferation that resulted in global warming surged renewable energy integrations. Additionally, peaking power plants are retiring and the driving factors of which are their age, emissions, and being less efficient [16]. The reduction of inertia due to the retirement of such units of scale and the inherent variability problem from Renewable Energy Resources (RES) require more flexibility in the power systems. However, the added flexibility must be economically viable respecting resources better and addressing system reliability constraints. As the need for electrical energy balancing service further increases, due to the variability of distributed energy resources (DERs), the significance of novel options in demand-side

management grows even more [1], [17]–[20].

Noteworthy assets for the Distribution System Operators (DSOs) are managing inherent flexibility in the demands which is a far better alternative to the expensive reserve generations or ancillary services. This distinction is obvious as DSM resources are inexpensive, emission-less, and spare no fuels [17]. Demand-side management programs offer reliable flexibility reserves and energy efficiency by reducing consumption during peak hours, load shifting or implementing various pricing mechanisms like time of use rates (TOU), critical peak rates, and real-time rates [21].

With the advent of modern smart grid technologies, distribution systems and demand control paradigms have been reshaped. Various utility-scale DR programs have been introduced with different application levels and prospects. The concept of DSM started around 1980 in many countries but for large scale industrial customers as an initiative for adding flexibility from the demands through manual implementation [21]. The loads were directly controlled by the utility with little or no customer interaction. However, DSM implementation required an initial customer consent. DallAnese et al. [22] extended the definition of flexibility by identifying residential, commercial, and district loads as the main reason behind the requirements for high flexibility resources such as distributed energy resource (DER) penetrations.

2.1 Application of Thermostatically Controlled Loads in the Demand Side Management

To bolster the growing acceptance of DR programs researchers started building physical load models to capture the underlying characteristic of loads consumption behavior [23], [24]. An extensive load modeling bibliographical library was provided by IEEE in 1995 covering relevant modeling approaches for various power system studies around the end of the 21st Century [25]. Classical load models that are used in power-flow simulations are termed as static load models and these models define load as a function of the bus voltage and frequency. Static load models have been implemented in industry-grade load flow studies for years. Various power system studies require different load models depending on the type of application and the load models.

Thermostatic Controlled Load models have been utilized in DR programs for various power system services. Various researchers have investigated physical-based space and water heating, Heating Ventilation and Air-Conditioning (HVAC) load models for the provision of DR services [26]–[29]. In [26] a model for TCLs has been developed to understand the load model’s potential response to extraneous inputs like the variation in electricity prices. In [27] the total TCL temperature setpoint has been manipulated while solving a statically mechanical model, to gain intuition to the system dynamics. Authors in [28] developed a modeling scheme to incorporate TCLs in wind power output error forecasting. Thermal storage capabilities of refrigeration systems have been employed in [29] to manage the peak refrigeration demand of a supermarket. The applied control scheme has shown to be able to sufficiently

compensate the overall refrigeration power peaks while maintaining the refrigerated temperature conditions within the predefined constraints. Peak demand reduction highly depends on the power demand ratio between other consumers and compressors because only the compressors' power is controlled. However, the preset peak demand limit needs to be selected with care because the combination of a very low-limit and long-peak demand of other consumers brings the refrigeration system to its temperature limits and the system may not be able to maintain the desired power demand. Also, the actual conditions within the supermarket need to be validated before selecting the peak limit, where the focus must be on historical peak demands for other consumers, peak durations, and the characteristics of the refrigeration system and stored food.

At the residential level, TCLs such as space and water heater are being inspected by researchers and aggregators alike [11], [30]–[32]. For example, the authors in [30] utilize TCL loads like water and space heaters in a district heating system coining the new controller as Electric Heat boosters (EHB) for integrating district heating and grid operation. Their results demonstrated low-temperature district heating while saving energy and achieved integrated DR for providing Frequency-Controlled Reserves for Normal (FCR-N) operation. However, their findings have a limitation due to the specific energy patterns of the local district. Their work is extensively relying on communication links between the nodes and a centralized station using a Message Queuing Telemetry Transport (MQTT) protocol which is a machine-to-machine protocol providing connectivity for IoT in a subscribe and publish fashion. However, communication adds extra costs and delays also, the MQTT protocol utilizes Transmission Control Protocol (TCP) which is developed for devices with large memory and

high computing power. Also, centralized brokers limit the scale of implementation due to additional overhead for each controller.

TCLs aggregation plays an important role in providing the necessary services for power systems operation. An optimal algorithm for aggregating the TCLs is presented in [11], where existing and new added TCLs are considered for providing Frequency-Controlled Reserves for Normal (FCR-N) service. Their optimal solution is for reducing the costs accompanying the communication infrastructure and DR control actions. They also manage to incorporate new TCLs without significant changes. They use recurrent neural networks for building the control algorithm that optimally predicts and manage the TCLs responding to DR signals and customers' usage uncertainties. However, prediction uncertainties are compensated by back-up resource activations which is partly a shortcoming that the back-ups must be constantly procured. They also base their work on communication, and their work cannot be generalized for the distribution system that lacks a well-established communication infrastructure.

A load-following DR algorithm is proposed that considers TCLs aggregation for the coordination of generating units [33]. Multiple TCL aggregators share the regulation proportion in a distributed manner. The aggregation of TCLs is further tuned up by adjusting their local setpoints. The distributed control of aggregating agents work in decentralized fashion for optimizing the reference temperature setpoints, i.e., guide the aggregators to track the reference power. However, such a strategy becomes prolonged and computationally intensive especially when the number of aggregators become large. Smart control strategies can mitigate power system imbalances but only through extensive communication reliance and detailed modeling of the system

loads. Furthermore, a separate communication network design is required for the centralized-distributed agents-based DR

2.2 Demand Side Management and Demand Response

DSM by the electric utilities through the traditional supply-side management paradigm included future electricity demands forecasting in the planning. The utility would then consider various supply-side options to meet the demand [34]. As the total demand and load variety increased, utilities' demand-driven planning became a difficult option thus, utilities initiated the concept and practice of load management through DSM. It is performed through different methods for obtaining various goals influencing the consumer load curve [35]–[37]. DSM first started with large customers, industrial and commercial, as large consumers bring significant flexibility in demand reduction with low cost. Direct load control (DLC) was the first method applied by utilities in the 1980s. Since then DSM through DLC has been used worldwide for load curve shaping. However, DSM earlier brought significant inconvenience to the customers as it included a unidirectional load control command without considering customers' real-time status.

The term demand response has been introduced lately with the emergence of smart grid technologies. DR is a customer action and choice-based program where the loads are controlled as per their preferences to achieve certain energy savings, voltage improvement, and price reduction targets. Modern trends in power systems

are shifted towards energy security and reduction in carbon footprint by promoting RES and energy efficiency programs. Demand response (DR) can be utilized for several benefits including peak shaving, reducing operation times of peaking units (top contributors to increased carbon footprints), and deferring investments in the transmission and distribution infrastructures. DR can be implemented in several ways. In price-based programs, changes in electricity consumption are obtained in response to variations in price. These are further categorized as a time of use rates, real-time pricing, and severe peak pricing programs.

In incentive-based programs, customers are offered incentives in return for allowing the utility or aggregator to control their loads. DR has been around for decades; load management programs and interruptible tariffs were introduced in the 1970s in many countries. These programs, however, were for large loads like industrial and commercial customers. For residential customers, direct load control was applied. This deployment was hampered by communication issues as the control had to be applied manually. In 1980, policymakers for utilities termed demand management as a reliability resource in their planning. The international energy crises of the 1970s and 1980s created much awareness regarding the potential role of DR. However, in the 1990s utilities and policymakers redesigned many vertically integrated industries for incorporating competitive wholesale-based markets and introduced customers' participation gradually [38]. For an optimal balance between generation and demand in recent times, the loads are shifted to times of low demands and high renewable generations.

As power systems evolved a renewed interest in DSM grew and two approaches

emerged for DSM namely a) time-based DSM and b) incentive-based DSM. The time-based DSM adjusts the electricity price by generation and demand scenarios and applies critical-peak pricing, time of use tariff, real-time pricing, and consumer credits for load reductions [39]–[41]. In the incentive-based approach, customers are rewarded if their demands are adjusted by an aggregator or utility company. In this approach the customer’s handover some level of control to the utilities. Some DSM included in the incentive-based approach are interruptible service, DLC, demand bidding, capacity market program, and ancillary service market. Both time-based and incentive-based approaches are feasible and have been successfully used in many studies [42]–[46]. However, sometimes the incentive-based DSM may be haphazard, leaving no room for customers’ priorities in the load management. That’s why consumer comfort must be evaluated as customers’ lifestyle disturbances may not lead to effective DSM application.

Efficient and robust DSM and DR programs exploit the potential local flexibility and provide voltage profile improvements, supply and demand balancing, and helps in the integration of distributed energy resources (DER), such as wind and solar PV [47]. Supply and demands are balanced by utilizing the flexible loads such as electric vehicles (EVs) or heating units with thermal storage [48], [49]. A general demand-shaping approach is applied that is suitable for putting a limit on the order bids to a day-ahead (DA) energy market. A distributed DR algorithm is then applied for the EVs in a theoretic game framework.

2.3 Centralized and Decentralized DR Controllers

Various centralized and decentralized approaches have been proposed for the implementation of demand response programs. A centralized control command signal is sent to the Air Conditioners (ACs) and the Electric Water Heaters (EWHs) for load following and spinning reserve services [50], [51]. In these approaches only AC and EWH dynamic models are simulated, however, real household appliances include disparate devices that may also perform well in DR associated services. They proposed separate decentralized control approaches for local voltage, local frequency, and electricity price signals in the dynamic models. Their DR control did suffer performance issues in communication delays between the system operator and appliances and due to these delays they used a decentralized approach for frequency regulation. Decentralized controllers offer a faster response, but its prediction is complex because a high order non-linearity may involve. The delay times for the decentralized controllers may vary between 0.1 to 1 second [52]. Centralized controllers may perform slower, but they are more robust and their relationship in terms of percent load reduction and its temperature setpoint adjustments is close to linear and the communication delay may lie in the range of 2.5 to 5 seconds [53].

A communication-based decentralized approach is applied for DR in [54] through the communication infrastructure of microgrid's smart meters. Their proposed algorithm determines local DR signals corresponding to the received price/incentive signals by the smart meters. Relying on strongly connected communication networks and prosumers' information exchange are some drawbacks that may not result in a

fully optimized decentralized controller. A novel blockchain-based decentralized DR approach is proposed [55] that integrates blockchain architecture with smart contracts for unlocking load side flexibility in terms of supply-demand balances. Their DR agreements must be validated since 100% renewable penetration is considered in this study, for this reason, they used a blockchain paradigm for ensuring a programmatic energy flexibility method. The peer-to-peer decentralized trading mechanism excludes DSOs that reduces energy transaction costs by real-time adjustments of the demands and the DR agreement validation. However, their approach is simulated only for UK consumer data sets that assumed a 100% distributed generation from solar PV. Multi-stakeholder markets exist, e.g., DSOs, transmission system operators (TSOs), and retailers that need to be included in the DR program if blockchain is used since blockchain use linked records through cryptography that will successfully coordinate the energy flexibility options.

In the recent times, DR has attained significant consideration by the private firms for a wide range of applications. KIWI power, a leading demand response aggregator in the UK, has generated significant revenues for large scale electricity customers since 2009. They have introduced DR programs at various levels in the distribution system. Their main objective is to reduce electrical demands during peak consumption hours providing required ancillary services to the grid. This creates a green and more cost-effective grid but other than the peak hours their costly smart infrastructure may not be used. The smart control devices can be used for continuous voltage profile improvements, paving the way for RES integration targets. Nevertheless, their setup reduces the need for inefficient backup power stations and provides frequency

regulation and secure supply to high priority customers [56], [57].

2.4 Conservation Voltage Reduction

A traditional approach for DR application is load management. For benefiting from the voltage-demand relationship in DR, traditional load management, on-load tap changer (OLTC), and capacitors are considered as common. Their potential for demand management is significant, and they are cost-effective. The control of real power consumption of the demand via voltage regulation devices is based on the fact that a considerable proportion of the demand is inherently voltage-dependent. For example, the real power consumed by resistive loads (e.g., water heaters) is proportional to the squared voltage at the load side. Hence, reducing the voltage by voltage-controlled devices can effectively reduce the power consumption of these loads. This process is called conservation voltage reduction (CVR).

Many studies have considered applying CVR via OLTC in substation transformers, i.e., at the distribution's primary side [58]–[60]. These studies have shown quantifiable benefits for this CVR approach for the US distribution utilities. Some studies highlighted OLTCs as the main control device for voltage-based DR, maximizing their benefits beyond voltage regulation [61]–[63]. They controlled more household loads with individual OLTCs installed in the distribution system. They also identified the percentage of voltage-demand management implementable with their reconstructed distribution transformers. However, their distribution transformers need retrofitting, which included large investments. Fei Ding et. al [64] explored the use of legacy

voltage regulating devices coordinated with smart inverters to increase the benefits obtained by OLTCs and capacitor banks. Advanced metering infrastructure (AMI), by Dominion Virginia Power, achieves 4% reduction in power during off-peak periods [65]. The innovation is in their metering, infrastructure avoiding the computational extensive modeling of the distribution network feeders. However, they accomplished CVR by OLTC through voltage feedback from the meters, which would require intensive investments in the AMI.

Shunt capacitors are considered for CVR studies, but they are not directly involved in CVR, however, they are assisting OLTC transformers [66], [67]. The capacitors flatten the distribution network voltage profile for the areas having the worst voltage issues. These areas are either far away or connected through a weak, highly loaded line from the substation. Some studies have considered static var compensators (SVC) and a consumer-level controller for voltage-led load management [68], [69]. Other researchers have investigated incorporating the voltage-dependent flexibility to demands that are not inherently voltage-dependent. For example, in [70], [71] the concept of electric springs (ES) is adopted for this purpose. ES is used to manage the consumption of non-critical loads by regulating its voltage while maintaining a fixed voltage across critical loads. This is performed by deploying a voltage source converter in series with the non-critical load.

2.5 EV as an important DR resource

The introduction of Electric Vehicles (EVs) in the automotive markets enlightened their crucial significance both in the general public and researchers. Since then, various research works [2], [72]–[78] have considered EVs for numerous power systems’ services. An autonomous EVs charge controller is simulated in [2], [73], [77] for the problems of voltage fluctuation. They have attempted to incorporate voltage-dependent flexibility to the EVs charging. In this case, each EV charger is equipped with a voltage-based controller that regulates the charging rate based on the voltage at the point of connection (POC). Basic autonomous voltage based EV charge controllers are suggested in [76]–[78]. Fairness is a major challenge for this communication-free voltage-based charging. That is if all charge controllers use the same voltage reference, the EVs connected downstream of a given distribution feeder will always be at a disadvantage compared to those connected upstream.

To address fairness, voltage sensitivity due to the change in load at the local POC is deployed in [2]. A layout of the controller at the customer site is shown in Fig. 2.1. Note that the voltage magnitude and its sensitivity have a complementary relationship. In other words, POCs with higher voltage magnitudes tend to have lower sensitivities to the load changes than POCs with lower voltages. EVs are considered by DR aggregators for frequency regulation [79], [80]. For providing an optimal frequency support an EV fleet is controlled. Both of these works utilize the inherent flexibility of the EV battery for providing regulation services. Battery swapping techniques for charge control are applied using heuristic methods, i.e., Particle Swarm Optimization

(PSO) to reduce charging expenses, system losses, and violations in nodal voltages.

Similarly, optimization methods like convex optimization approaches are used for minimizing power distribution system components stresses by controlling EV charging [81]–[83]. The aggregator ensembles EVs power demands and transmits signals to the controllers in a centralized way. The autonomous Vehicle-to-Grid (V2G) strategy in [83] is used for providing distributed spinning reserves responding to the system conditions. However, this controller collects users' household consumption pattern for maintaining fairness and voltage control. Also, the system nodes are treated balanced that doesn't depict true secondary distribution systems and it may result in unacceptable results.

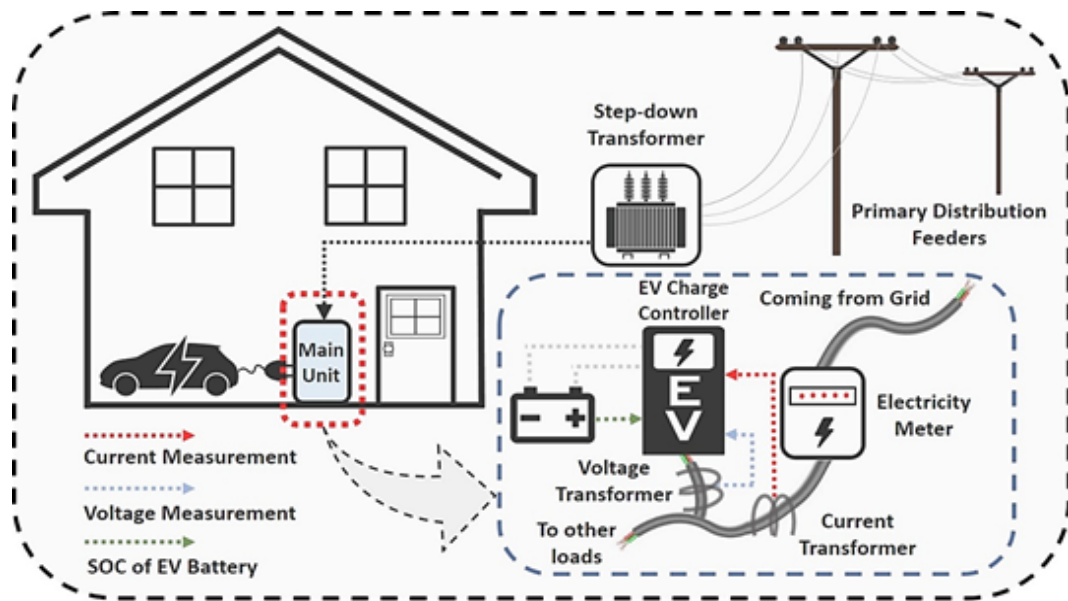


Figure 2.1: Decentralized autonomous EV charger layout at the customer site [2].

2.6 Essence

Various Demand Side Management (DSM) techniques are studied and implemented in the literature that focus on various services for the power distribution systems. The Centralized DR techniques are best in performance for management of the aggregated loads. However, these strategies rely on extensive communication networks. The decentralized DR techniques are better in performance and these techniques rely on reduced communication networks. Autonomous DR approaches have a good performance and are communication-free. Communication-free control frameworks are the fastest due to their local control actions.

A space heating TCL load model of a prevalent modeling presented in [84] is incorporated in the DR controller. The purpose of utilizing this model is that it has been validated by running the model with input parameters from the residential houses in Virginia, US. As such physically verified models test the full potential of the proposed communication-free demand response controller in improving voltage profiles and maintaining user comfort in terms of the temperature profile settings.

CHAPTER 3

PROPOSED CONTROLLER APPROACH

A machine learning-based DR control strategy is proposed that utilizes estimated load nodes' online sensitivity and nodal voltages. The controller incorporates TCLs load model as it has general applicability while the concept of artificial intelligence has been applied to improve the controller's performance, i.e., fairly managing TCLs connected at various locations in the distribution system. The use of fully connected MLP neural network enables the controller to effectively mitigate the voltage violations while keeping the houses' temperatures within the permissible range for all the end-users irrespective of their locations.

The machine learning-based autonomous controller incorporates a transfer learning idea that is utilized for framing a communication-free development. Nodal voltages and their voltage-to-load sensitivities are given as input signals to the controller. Several re-trainings are performed for capturing the uncertainties of the end-users'

TCL usage pattern. A part of the trained network's output is utilized in re-training such that the DR controller becomes adaptive to various system conditions. Collecting all possible load variations, for deriving optimum TCL power caps, while keeping track of the end-user temperature profile ensure fairness among the nodes. Also, the controller maintains voltage standards of the American National Standards Institute (ANSI) of the type C84.1-2006.

3.1 Real-Time Online Sensitivity Update

The main idea of the proposed control scheme is to adjust TCL power consumption at various load nodes in the distribution system keeping track of the connected users' temperature profiles that is an indicator of the customers' comfort. Adjusting TCLs while ensuring customers' temperature bounds, and safe voltage operation limits, i.e. 0.95 p.u.-1.05 p.u., is a top priority by the ML-based control approach. Therefore, a local online measurement for nodal voltage and sensitivity of the node are made if a change of 5% occurs in the load using (3.1) that is proposed in [2].

$$\delta(t) = \frac{v_i(t + \Delta(t)) - v_i(t)}{p_i(t + \Delta(t)) - p_i(t)} \quad (3.1)$$

Where δ_i is the nodal sensitivity, Δt is the time interval, v_i is the node voltage in volts, and p_i is the nodal power demand in MWs.

This sensitivity estimation approach doesn't rely on full observation of the network or remote monitoring. Furthermore, the sensitivity is updated at each node autonomously whenever there is a significant change in the load. In this strategy,

the voltage and demands (i.e., active and reactive or apparent power) at the specific node are measured online and the sensitivity is updated to incorporate changes in the system conditions. Although the proposed sensitivity approach captures the system variations effectively, few points are worth mentioning related to the proposed approach. According to the equation (1), the sensitivity may become positive or negative. In fact, the voltage variations at a bus is in a strong proportion to the load variations at that specific bus than to other system buses [7]. Therefore, a nodal voltage usually increases/decreases when the load at that bus drops/adds. Such scenarios result in negative sensitivity values which will occur most of the time due to significant changes in the cyclic loads (i.e., a change of 5% in the load).

3.1.1 Positive Sensitivity Values

When load or voltage changes accordingly in proportion this results in positive sensitivity values. As a fact, load increase at a load node decreases the voltage at that specific node. Interestingly the decrease in load at other buses may increase the voltage at this specific node, and hence sensitivities are positive. However, occurrence of such variations at other nodes, at the same time, is very seldom. Moreover, notice that the load variations effect at the bus of consideration will be more pronounced as compared to when the changes occur on other nodes in the system [85]. So, in the controller strategy online sensitivity estimation at any node is made only when changes are greater than a specific threshold i.e., 5%.

3.1.2 Thermostatically Controlled Loads Model

The proposed strategy incorporates space heating TCL load model of a prevalent modeling technique presented in [84]. The purpose of utilizing this model is that it has been validated by running the model with input parameters from residential houses in Charlottesville, Virginia, USA. As such, physically verified models truly test and validate potential of the proposed communication-free DR controller in improving voltage profiles, maintaining fairness and user comfort in terms of temperature profile.

The space heating TCL model is based on the balance of thermal energy between the heater and the surrounding environment and indoor air mass. When the space heater is operating, the electrical energy is converted to thermal energy that is stored in the room's air mass. The temperature of this room will change following the heat exchanges between the room and the surrounding. The Heater will be running at its operational rating in steps of ΔP_i kW up to a maximum aggregated value of ΔP_T kW when required to raise the temperature of the air mass. The temperature will be kept within the bounds of $\pm\Delta T$ °C around a specified set point. Thus, the indoor temperature will be fluctuating around a certain setpoint temperature T_s , and the temperature will be allowed to deviate within a dead band of $\pm\Delta T$ °C. In the case that indoor temperature is lower than the ambient temperature outside, the SH will be on, i.e., it will be compensating for the heat loss to the external surroundings. For example, as the room temperature goes below $T_s - \Delta T$, the SH will be turned on and the indoor temperature will start to increase gradually. The SH will be turned off at the instant when the room temperature goes above the $T_s + \Delta T$ threshold. The SH

will maintain throttling in its previous states while the indoor temperature is within a range of $T_s - \Delta T < T_i < T_s + \Delta T$.

The TCL status at any time instant is calculated as follows:

$$w_{AC,i} = \begin{cases} 0, & T_i > (T_s + C_{AC,i}) - \Delta T \\ 1, & T_i < (T_s + C_{AC,i}) + \Delta T \\ W_{AC,i-1}, & (T_s - \Delta T) \leq T_i - C_{AC,i} \leq (T_s + \Delta T) \end{cases} \quad (3.2)$$

Where $C_{AC,i}$ represents the controller's signal to the SH unit at the time instant i ($^{\circ}\text{C}$). The block diagram of the space heating TCL model is shown in Fig. 3.1 .

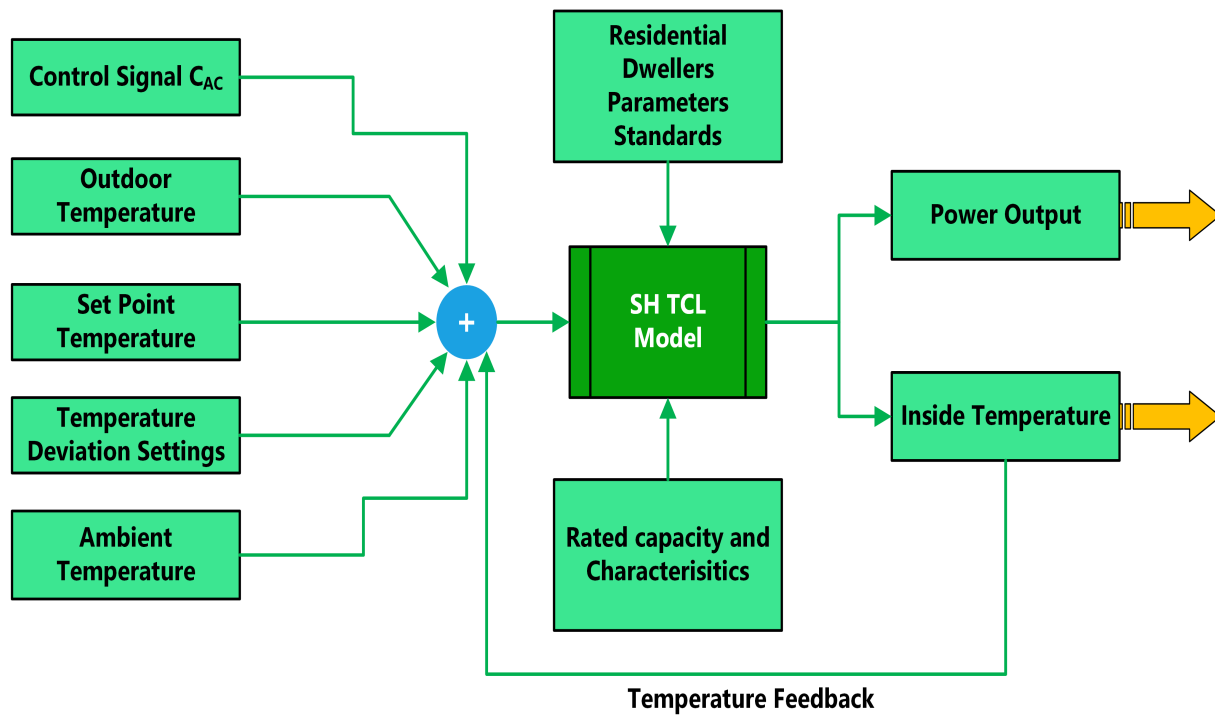


Figure 3.1: TCL Model employed by the DR controller for verifying power adjustments and temperature bounds.

3.2 Machine Learning-Based Training

Neural Networks (NN)-based ML approach employ non-linear statistical models that can be used to envelop the complex behavior of engineering processes—a top reason for their inclusion in the autonomous systems. The procedure of online measurement, from the power-flow simulations, is repeated for light and heavy loading conditions to cater to myriad variations from the TCLs usage pattern. To enforce a fair contribution from all the nodes, at any given state of the system, TCL power caps applied by the controller must maintain the temperature of the connected users within the allowed temperature range. The network is trained with all the data to obtain weights at the input, output, and associated biases, i.e., controller parameters. In this work, the sigmoid activation function given in (3.3) is employed by each neuron at all the layers of the network except at the output node, which is linear as given by (3.4).

$$\varphi(\omega) = \tanh(\omega) \quad (3.3)$$

Where φ is the transfer function, and ω is the output of the input layer calculated as,

$$\omega = \sum_{i=0}^m (W_i \times v_i + W_s \times \delta_i + b_i) \quad (3.4)$$

Where ω is input to the first layer neurons, W_i is the input weight vector, v_i is the

input voltage vector, δ_i is the sensitivity vector, and b_i is the input bias.

And $\tanh(\phi)$ is given as,

$$\tanh(\varphi) = \frac{e^{-\varphi} - e^{\varphi}}{e^{-\varphi} + e^{\varphi}} \quad (3.5)$$

Detailed steps for the data preparation and ML-based training are illustrated in the flowcharts of Fig. 3.2 and Fig. 3.3.

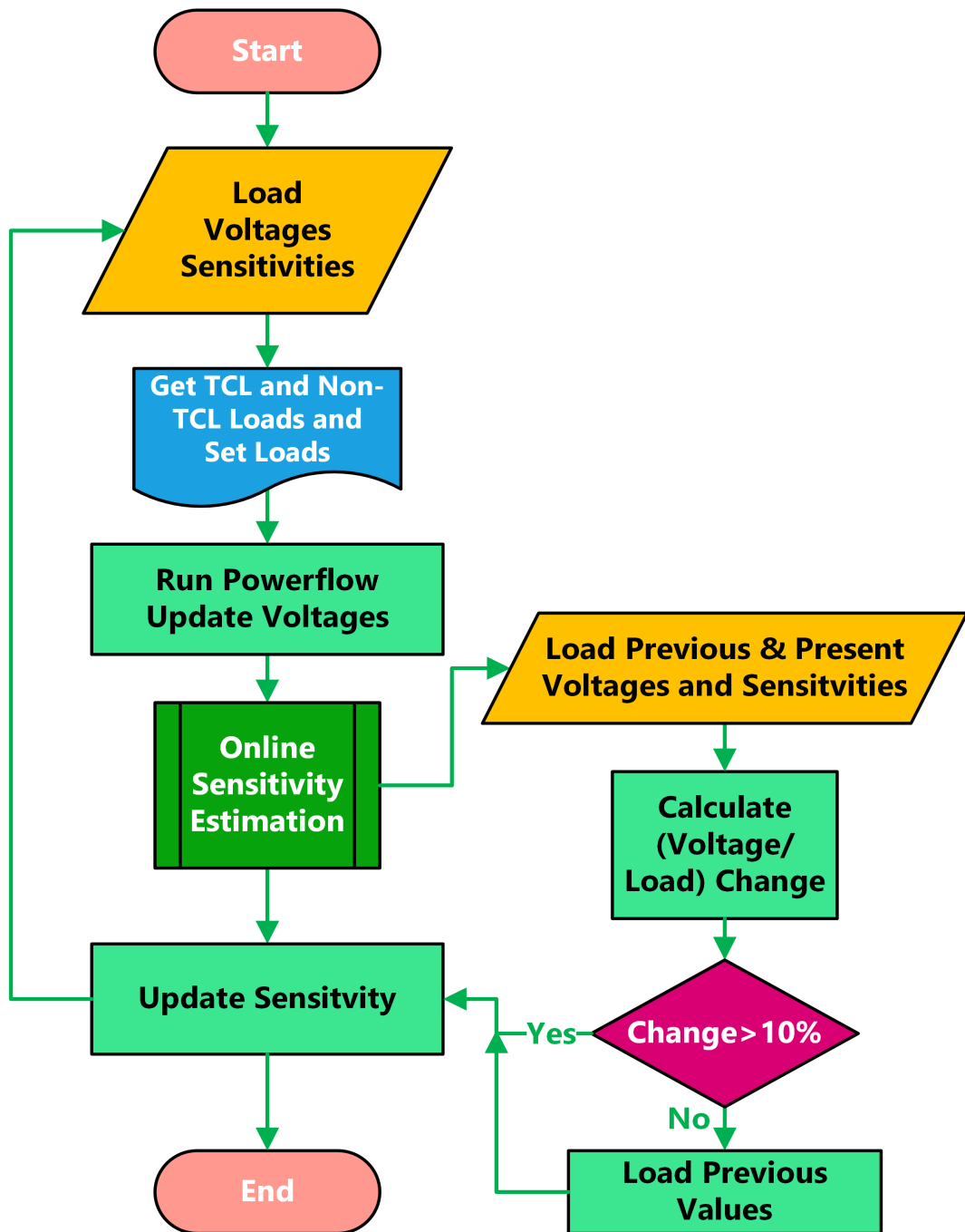


Figure 3.2: Data preparation for the MLP NN-based training flowchart.

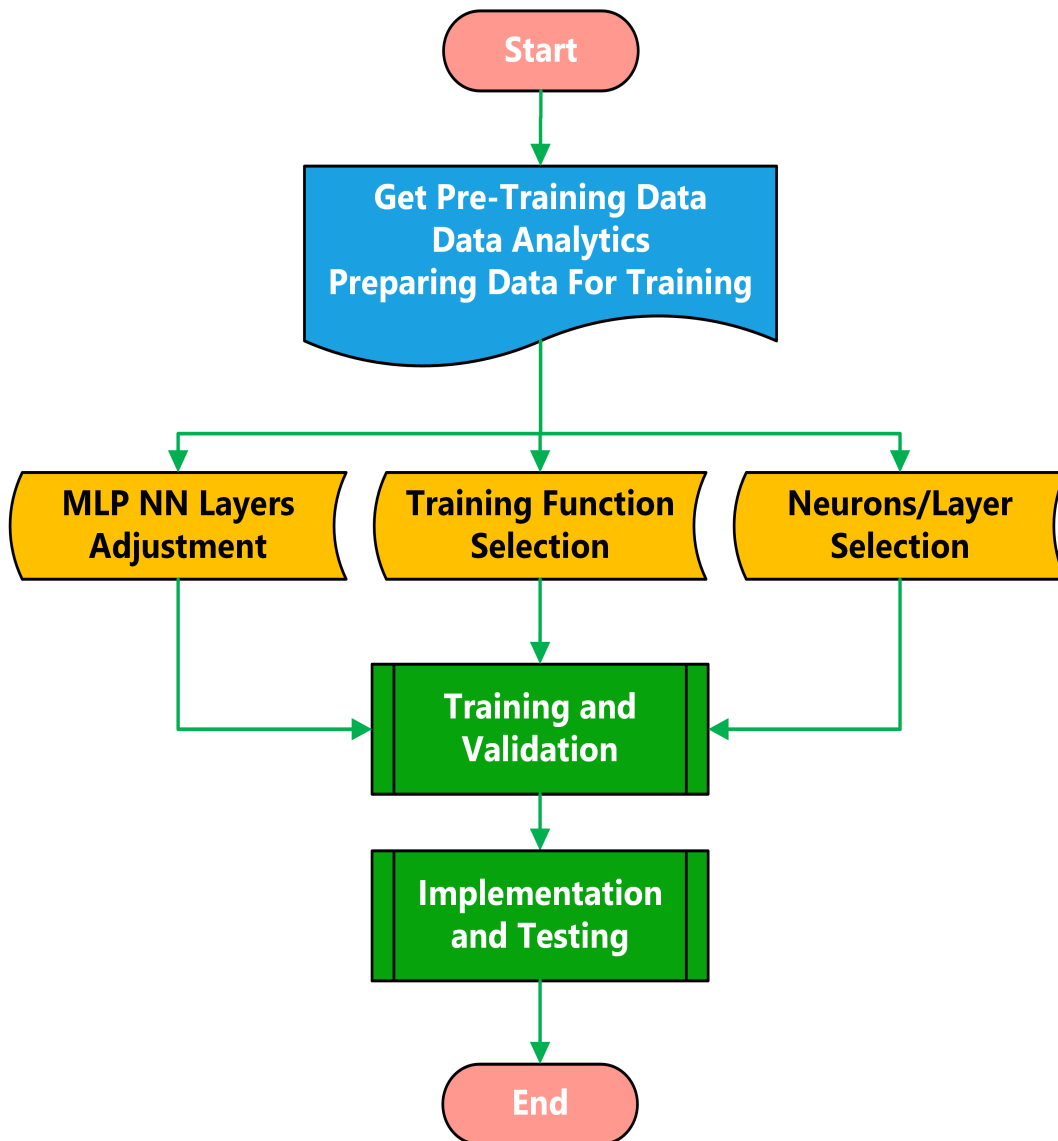


Figure 3.3: Training steps for the MLP neural network.

3.2.1 Employing Neural Network-based learning

Artificial Intelligence (AI) and Machine learning (ML) is at the forefront of many leading applications. From self-driving to heavy industrial complexes rely on the universal nature of these innovative algorithms. Neural Networks, a widely applied ML technique, easily regenerate complex patterns inherent in the ginormous data sizes. Since power systems generate extensive real-time data thus, data analytics in the emerging smarter grids will manage most of the distribution grid operations. Random flexible load usage, if left uncontrolled will become problematic for the DSOs. Voltage and online sensitivity estimation at the load nodes of the test distribution system are utilized as the decision parameters for the Multi-Layer Perceptron (MLP) Neural Networks (NN) to devise control strategy for the flexible loads. Thermostatic loads are readily dispensable and that are managed by the proposed DR controller

3.2.2 Data Assembly

The input parameters for the load model are selected as per the load model's specification for real houses in Virginia, US [84]. Fig. 3.1 shows the block diagram of the proposed TCL model. The model takes consideration of the room parameters such as the number of house dwellers, room structure, surroundings, and the heating unit electrical characteristics highlighted in Table 3.1. Equations (3.6),(3.7), and (3.8) describe the model attributes based on the input parameters.

$$T_{i+1} = T_i + \Delta t \times \frac{G_i}{\Delta c} + \frac{C_{HVAC}}{\Delta c} \cdot W_{AC,i} \quad (3.6)$$

Where T_i , is the room temperature in $^{\circ}\text{F}$. Δt is time unit in hours, G_i is heating gain during time unit in Btu/h , C_{HVAC} is heating capacity in Btu/h , Δc is the energy needed to change the air temperature by 1°F ($\frac{\text{Btu}}{^{\circ}\text{F}}$) and is defined as:

$$\Delta c = C_{air} \cdot Vol_{room} \quad (3.7)$$

Where, C_{air} is Specific heat capacity of typical room air 1.012 J/Gk or $0.0195 \frac{\text{Btu}}{\text{ft}^3^{\circ}\text{F}}$, Vol_{room} is the Room volume in ft^3 . The heating gain is calculated as follows:

$$G_i = \left(\frac{A_{wall}}{R_{wall}} + \frac{A_{ceiling}}{R_{ceiling}} + \frac{A_{window}}{R_{window}} \right) \cdot (T_{out,i} - T_i) + SHGC \times A_{windowsouth} \times H_{solar} \times \gamma + H_p \quad (3.8)$$

Where, A_{wall} , $A_{ceiling}$, A_{window} , are the areas of the wall, ceiling, and the window of the room (ft^2). R_{wall} , $R_{ceiling}$, R_{window} , are the thermal resistances of the wall, ceiling, and window of the room, $T_{out,i}$, is the outdoor temperature at time unit i ($^{\circ}\text{F}$), $SHGC$ is the Solar Heat Gain Coefficient, H_{solar} is the solar radiation thermal power measured in Wh/m^2 , and γ is a measurement constant. Temperature values in $^{\circ}\text{F}$, are converted to Degree Celsius ($^{\circ}\text{C}$) by using:

$$^{\circ}\text{C} = \frac{(^{\circ}\text{F} - 32) \times 5}{9} \quad (3.9)$$

The model parameters are given in the Table 3.1.

Parameter	Value
A_{wall}	3086.4 (ft^2)
$A_{ceiling}$	9600 (ft^2)
A_{window}	440.90 (ft^2)
R_{Wall}	13 – 15 ($\frac{^{\circ}F \times ft^2 \times h}{Btu}$)
$R_{Ceiling}$	38 – 60 ($\frac{^{\circ}F \times ft^2 \times h}{Btu}$)
R_{Window}	0.8 – 1 ($\frac{^{\circ}F \times ft^2 \times h}{Btu}$)
$SHGC$	0.71
C_{HVAC}	3412.14 ($\frac{Btu}{kWh}$)
H_{solar}	140 ($\frac{Wh}{m^2}$)
γ	$\frac{3.412}{10.76}$ ($\frac{Btu.m2}{Wh.ft^2}$)

Table 3.1: Residentail Household Parameters For The SH Load Model.

3.2.3 Methodology

A basic analysis of the test system is carried out with the TCLs from the load model simulation. The initial analysis is performed both for light and heavy system loading to assess the available room for the TCLs. This pre- DR controller simulation determines applicable temperature setpoints and the need for any initial deployable TCL caps. The proposed control strategy introduces a novel approach by controlling the temperature deviation ($\Delta T_{\text{dead band}}$) of the dwellings through the SH loads. The DR signals are finally configured and tweaked in the proposed strategy while end-users' discomfort is avoided. Priority for the non-TCLs stays intact by the controller. Voltage, online estimated sensitivity, and required TCLs are derived from the system light and heavy loading simulation. Around 80% light loading and 80% heavy loading data, chosen randomly, is utilized as input data for the MLP network while the network is tested within the MATLAB-DIGSILENT interface. Levenberg–Marquardt (LM) algorithm is used for training. LM is a fast and stable algorithm that has a stable convergence used for training artificial neural networks. The LM algorithm is a blend of the Gauss-Newton and the steepest descent algorithms. It adopts the celerity of the Gauss-Newton and stable approach of the steepest descent method. The NN structure employed, training, and testing performance are depicted in Fig. 3.4, 3.5, and 3.6 respectively.

The Mean Square Error (MSE) reduces as more epochs are performed through the training stage, however, it might gradually increase if over-fitting is done on the

training data by the validation process. The training stops if consecutive increases occur in the validation error check, and the best is derived from the epoch that have the lowest validation error as shown in Fig. 3.5. The blue, green, and red line show training, validation, and testing. The best line, plotted as dotted, mean that all curves should lie on the top of or close to the green curve, and this indicates successful training. Convergence occurs when the three curves cross or pass through the green dotted line in Fig. 3.5. Training state plot in Fig. 3.6 represents the progress or status of the training process during each epoch. Gradient curve is a value of backpropagation error gradient at each epoch in a logarithmic scale. A value of 10^0 means that the training has reached to the local minimum of your target function. Mu in the train state plot is a Levenberg-Marquardt (LM) adaptation parameter for the optimization process of the hessian matrix. A validation check error means an overfitting scenario and a zero-validation error means successful training. The training is stopped after six consecutive validation failures. Once the network training is finished, the trained model in MATLAB is interfaced with DIgSILENT simulation platform for testing and evaluation of the DR control strategy.

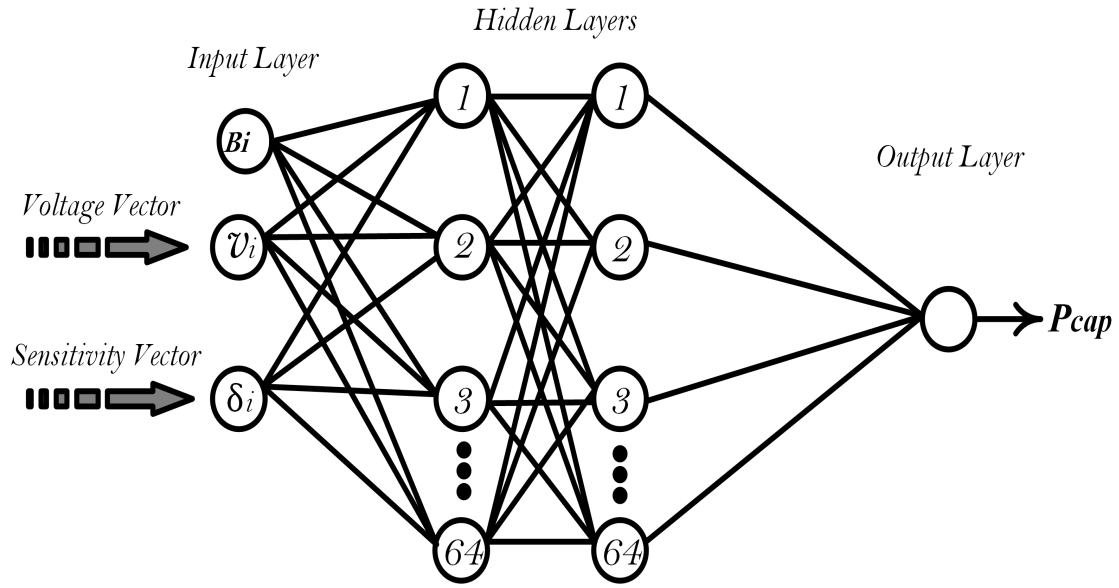


Figure 3.4: A figure of the used NN structure with inputs and outputs depiction.

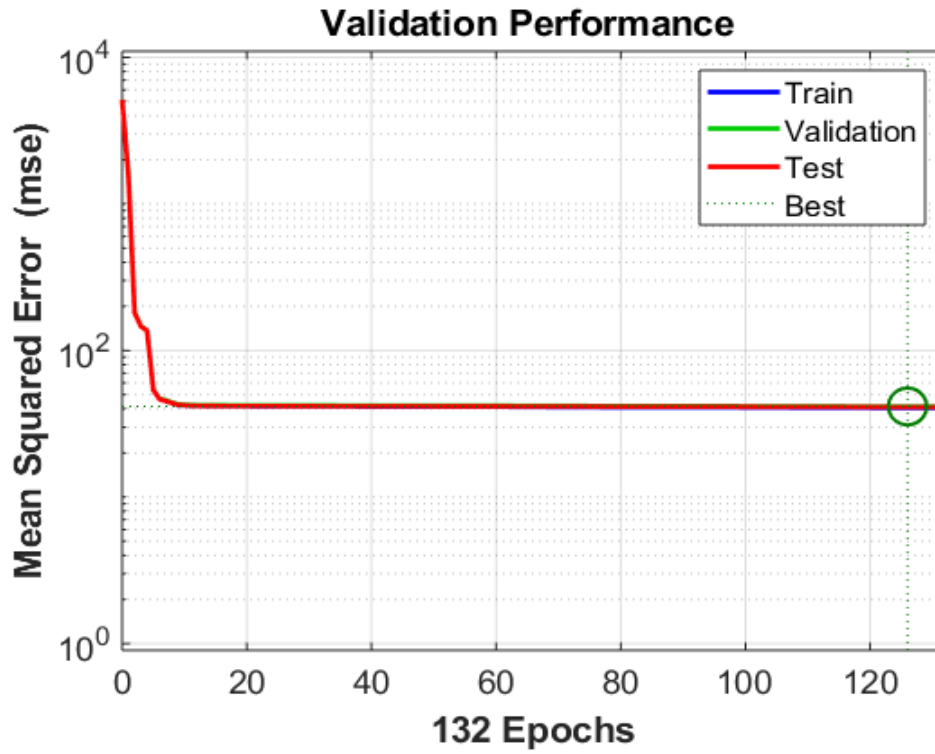


Figure 3.5: Training performance of the neural network.

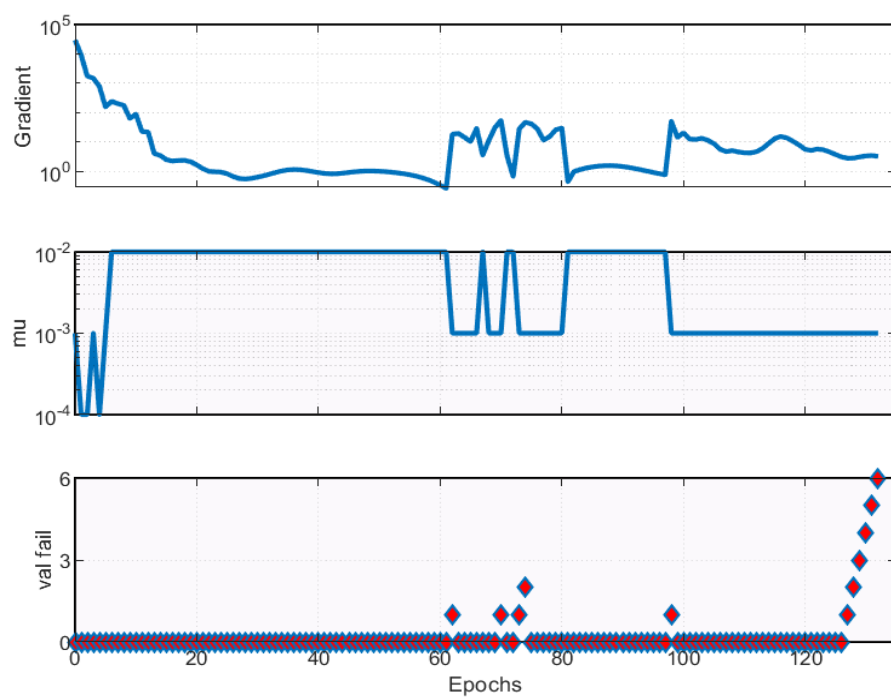


Figure 3.6: Final training state and validation achieved by the neural network.

3.3 Proposed DR Controller

The TCL-based controller will throttle power consumption of the TCLs when required, i.e., responding to system conditions. The machine learning-based proposed controller incorporates TCLs autonomously using a transfer learning idea that is utilized for framing communication-free development. Nodal voltages and their voltage-to-load sensitivities are utilized as input signals to the controller. Several re-trainings are implemented for capturing the uncertainties of end-users TCL usage patterns and the distribution system characteristics. Capturing possible load variations for deriving optimum TCL caps while keeping track of the end-user's temperature profile ensure fairness among the nodes. The test distribution system in [2] is considered to evaluate performance of the proposed controller. A noteworthy property of the controller is that it effectively regulates the system voltages within the acceptable range as defined by the ANSI C84.1-2016 standard. A detailed strategy of the autonomous DR controller is illustrated in Figs. 3.7 and 3.8, that shows the overall logic flow of the controller.

The DR controller will take local measurements for voltage and sensitivity to determine effective TCL power caps. While training the DR controller, different loading conditions are considered to incorporate various system conditions. The most important aspect of the proposed controller is to guarantee similar contribution from the end-users' TCLs that are present at different nodes in the distribution system for maintaining the system voltage and temperature profiles.

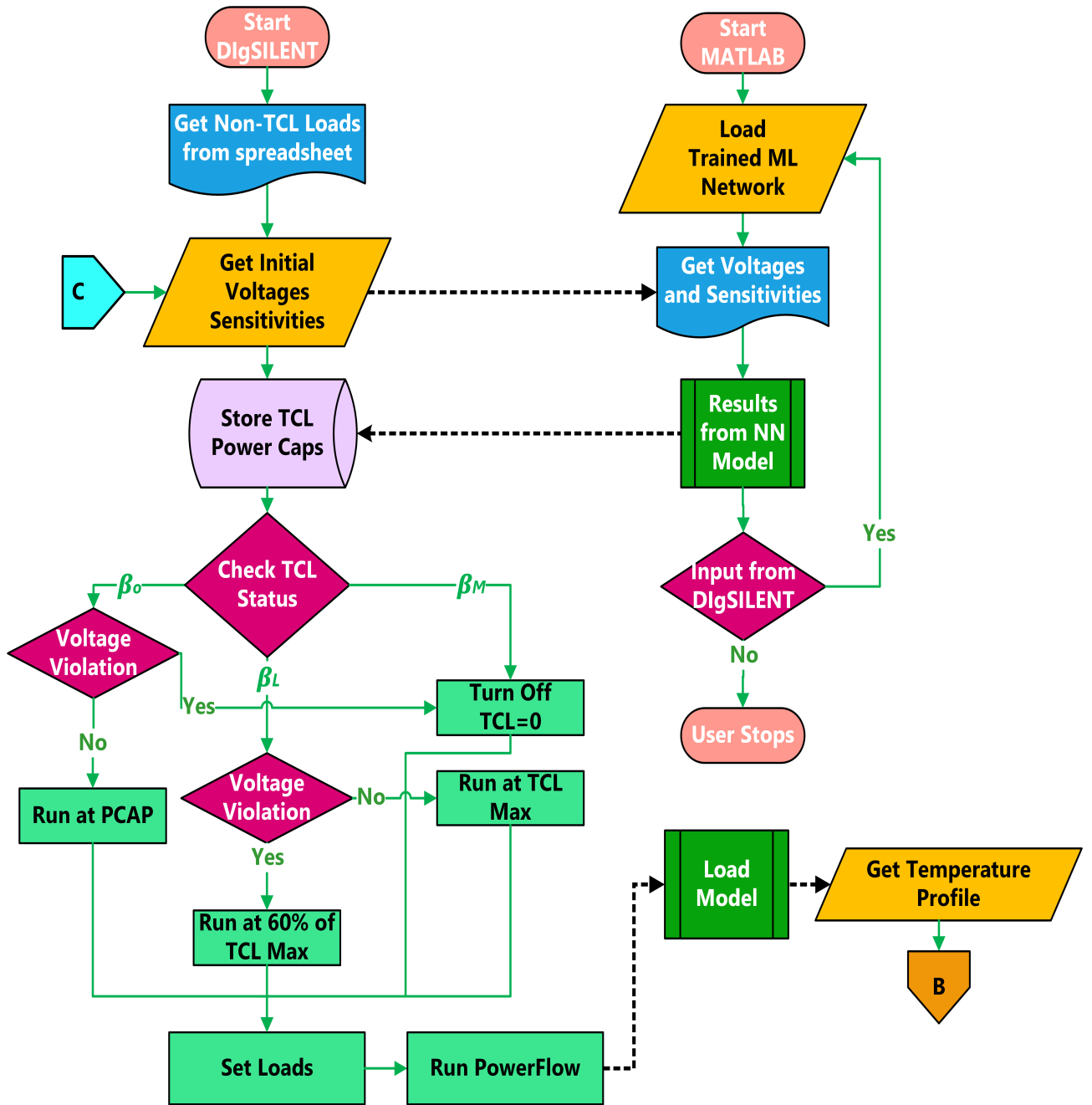


Figure 3.7: A detailed layout for the autonomous DR controller's strategy.

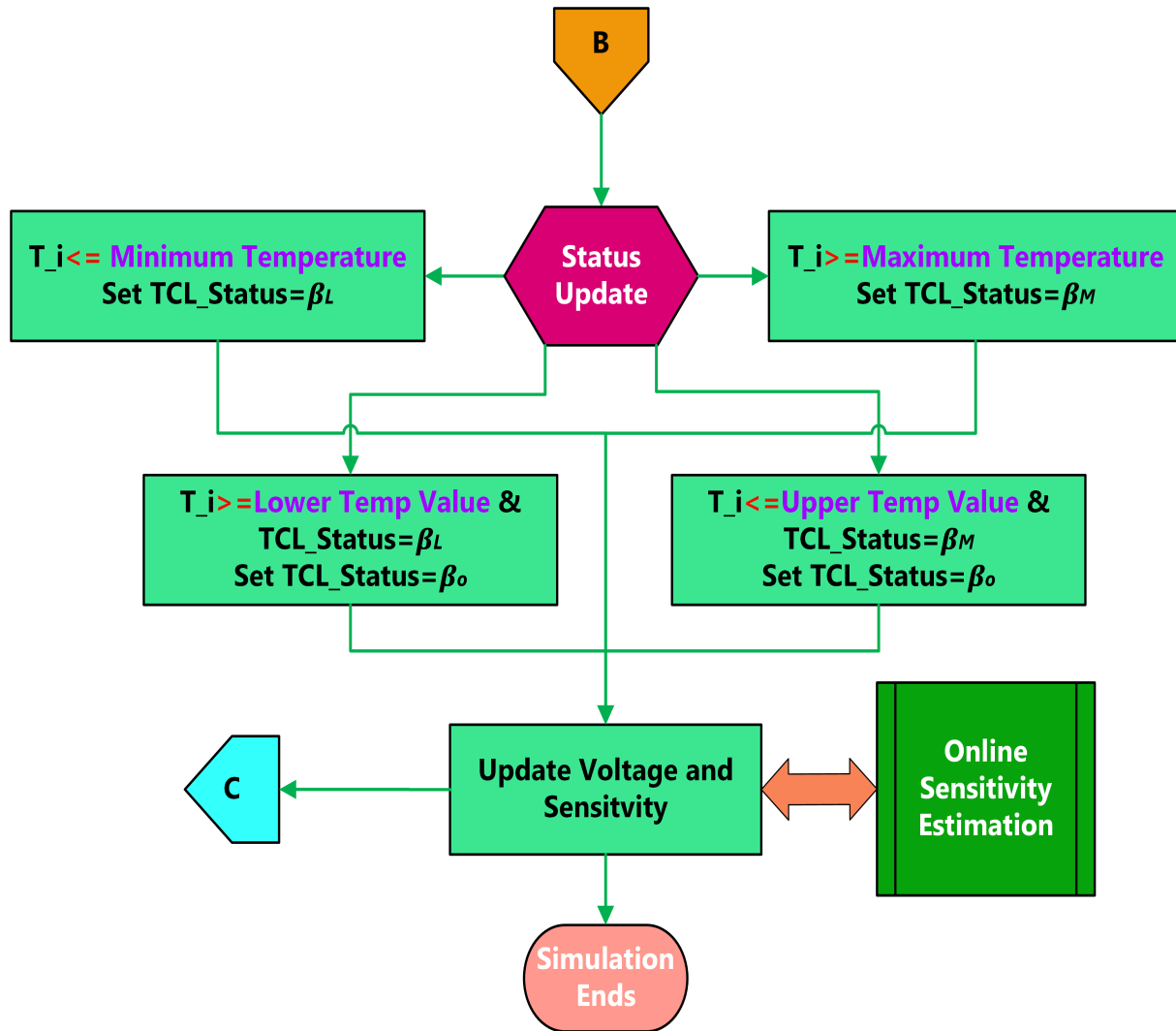


Figure 3.8: DR controller's control strategy layout continued.

3.3.1 Control Strategy

The controller checks initial voltages and sensitivities of the node and transfer them as inputs to the MATLAB for getting the trained NN model's output. After receiving MATLAB outputs, the DR strategy in DigSILENT checks previous TCL status for each connected TCL. There are three TCL states considered in the proposed approach. TCL status β_o means the TCL can be either turned on or off, and at this state the node temperature profile is within the temperature bounds, i.e., $T_s - \Delta T < T_i < T_s + \Delta T$, where T_s is the temperature setpoint pre-determined by the end-users and ΔT is the temperature range. TCL state β_L means the lower temperature boundary is reached in the previous instants and hence, the TCL must be operated at full load, i.e., TCL maximum rating. However, during TCL status β_L , if a voltage violation appears in the system the control strategy limits the TCL power to P_{limit} of the maximum TCL rating in order to ease the voltage violation. The reason behind choosing this specific reduced rating of P_{limit} is to avoid further temperature drop as a value below this rating may lead to temperature violations. Similarly, TCL status β_M , means that the upper temperature boundary is reached in the previous instants and thus, the TCL must be kept off. In order to avoid sudden surge in system demands the TCLs are allowed to change their consumption in smaller steps of certain threshold power, i.e., $\Delta P_{threshold}$ kW.

During TCL status β_o at any specific node in the system, the DR controller verifies that there are no voltage violations at that node. For example, if the autonomous controller faces a voltage violation it will intelligently turn off the TCL to ease the

system stresses and mitigate voltage violations while keeping track of temperature profile at that node. However, if there is no voltage violation at a node the DR controller will apply optimal TCL power cap, obtained from the trained model such that the user's temperature stays within the permissible limits. After setting TCL and non-TCL loads, the set TCL power caps are given to the TCL model to update TCL status and temperature profiles. The TCL status is updated as follows:

- 1-** If the current temperature of a specific node, i.e., connected customer, hits the minimum temperature bound, its TCL status is set to β_L . The minimum temperature bound is $T_{min}^{\circ}\text{C}$.
- 2-** If the current temperature of the specific node reaches the maximum temperature bound, i.e., $T_{max}^{\circ}\text{C}$, the TCL status is set to β_M .
- 3-** If the current temperature is less than or equal to the upper temperature value ($\theta_U^{\circ}\text{C}$) or greater than or equal to the lower temperature value ($\theta_L^{\circ}\text{C}$) the TCL status is set to β_o . Once the temperature profile and TCL states are updated the simulation proceeds to the next iteration as outlined by the off-page connector C in the flowchart of Figs. 3.7 and 3.8.

CHAPTER 4

SYSTEM INFORMATION AND DATA

4.1 Distribution System Under Test

To train, implement, and validate the efficacy of the proposed DR control framework in deploying the controller actions, a radial test distribution system consisting of various primary and secondary nodes is considered, as shown in Fig. ??and 4.2. This is a balanced three-phase system having 17 nodes and primary line-to-line voltage of 12.47 kV. Secondary distribution transformers at each primary node steps down the voltage from 12.47 kV to 0.22 kV. Each secondary transformer has 5 LV nodes and each LV node has 4 customers connected per phase, LV three-phase total customers are portrayed in Fig. 4.3. Test distribution system's parameters are tabulated in Table 4.1

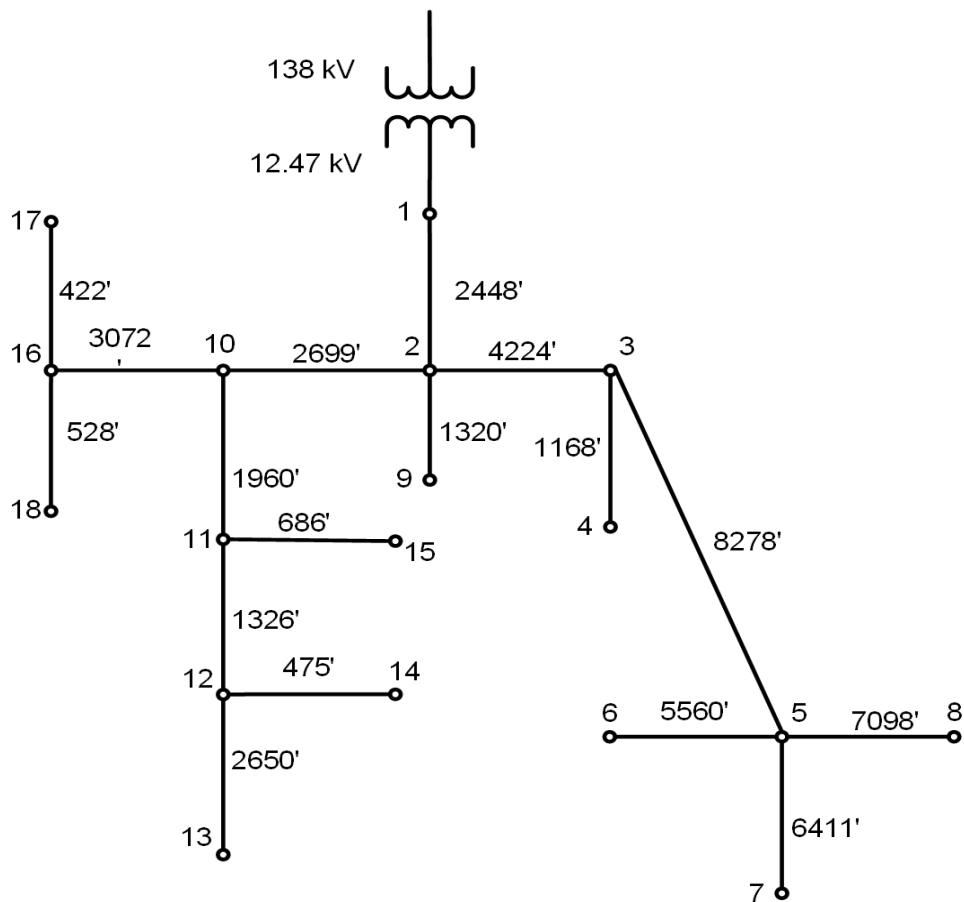


Figure 4.1: Primary Distribution Test System.

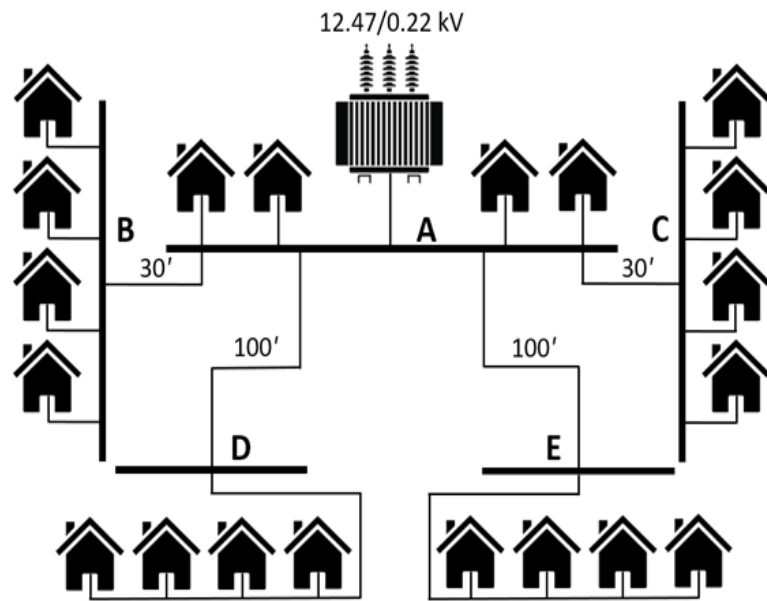


Figure 4.2: Secondary node layout in the distribution system.

Sr. No.	Description	Value
1	Phase conductor	ACSR 2
2	Neutral wire	ACSR 4
3	Primary conductors ampacity	180 Amps
4	Service Transformer rating	150 kVA
5	Secondary nodes conductor	350 Al 4/0
6	System frequency	60 Hz
7	Customers per secondary node	12

Table 4.1: Description for the Test System used in simulations.

4.2 Demands

Two types of demands exist in the system: 1) Non-controllable demands and 2) TCLs which are controllable loads. The non-controllable demands include household loads which cannot be used as DR resource. Real household load profile is used as non-controllable load. The TCL load profile is derived from the TCL model, that is a physical measurement-based load model made for Charlottesville country in Virginia, US [84]. The effectiveness of the proposed DR controller is evaluated under various loading conditions such as light and heavy system loading conditions. The motivation behind the inclusion of these loading states is to consider daily, monthly, and seasonal variations in the system demands.

4.3 DIgSILENT PowerFactory

The simulation platform used for the modeling and testing the proposed controller is Digital Simulation of Electrical Networks (DIgSILENT) Powerfactory 2020 [86]. PowerFactory is one of the leading power system software analyzing generation, transmission, and distribution networks. The software package used is licensed from DIgSILENT GmbH, Germany and includes full functionality features like highly intricate and state-of-the-art including wind power, DGs, and EVs. PowerFactory is fully Windows compatible and easy to use that ensembles reliable and flexible modelling techniques novel algorithms and multi-user database idea. Also, with its added flexibil-

ity for DIgSILENT Scripting Language DPL and interfacing, PowerFactory is highly suited to fully automated and embedded applications like DSM in the distribution grids. Different phasing schemes can be implemented, whereas in the proposed controller a classical three-phase system have been created as distribution power systems and majority of the LV electrical networks employ them. The secondary nodes after each primary are termed as A, B, C, D, and E as represented in the Fig. 4.3 as 02A, 02B, 02C, 02D, and 2D for the secondary distribution system node 2.

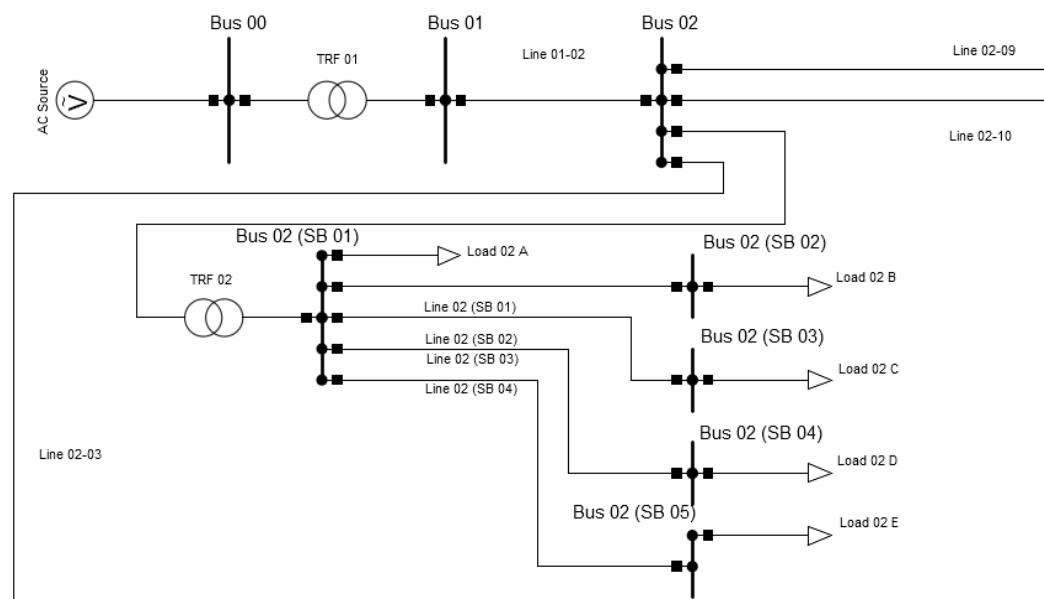


Figure 4.3: A portion of the Test Distribution System created in DIgSILENT Powerfactory.

CHAPTER 5

RESULTS AND DISCUSSION

Different system loading conditions are assumed for evaluation of the DR controller's performance and results. Some of the results presented and discussed are system-wide, while some are node-specific, i.e. nodes 2A, 2E, 8A, and 8E. These nodes are located at the upstream and downstream areas in the system, that's the reason they are considered to assess the fairness of the DR control actions among the system LV nodes. Given that there are numerous system cases and results, thus, for compact demonstration, node-specific simulation results are confined only to sample nodes that serve as system representatives and can provide enough details for the controller's performance assessment.

5.1 Base Case Non-TCLs and TCLs Results

To test the performance of the DR controller various loading conditions such as light and heavy loading conditions are considered. The purpose of these loading states is to consider daily, monthly, and seasonal variations in the system demand. Node 2A and

8A are the distribution system's upstream nodes while 2E and 6E are the downstream nodes. The Non-TCL load profile for Node-2A, Node-2E, Node-8A, and Node-8E and total system load profile are shown in Fig. 5.1 and 5.2, respectively both for heavy and light loading system conditions.

The TCLs profiles for Node-2A, Node-2E, Node-8A, and Node-8E are shown in Fig. 5.3. In this figure, the upper subplot highlights the TCLs profile for Node-2A and Node-2E. Similarly, the lower subplot shows the TCLs profile for Node-8A and Node-8E. The outside ambient temperature is plotted in Fig. 5.4. The voltage profiles for the system base case, i.e., without any DR controller's implementation are plotted in Fig. 5.5. It can be clearly observed that the Node-2A always has a higher voltage than that of Node-2E and similarly, Node-8A always has a higher voltage than that of Node-8E since these nodes are near the transformer and on the same radial feeder as depicted in Figs. 4.1 and 4.2. Thus, these upstream nodes, i.e., Node-2A and Node-8A have higher voltages. From the voltage profile plot during heavy loading, the impact on voltage profile is evident, the voltage violations are sustained for longer time periods. The approximate temperature profiles for the specific nodes are depicted in Fig. 5.6. Since the TCLs are lumped and the temperature response is obtained through the TCL model that's why this figure nearly represents the aggregate temperature. In actual the response would variate around $25 \pm 1.5^{\circ}\text{C}$. In fact many base case temperature profiles are possible depending on the behavior of the assumed TCL characteristics. It can be seen that the temperatures always remain with the allowable temperature range.

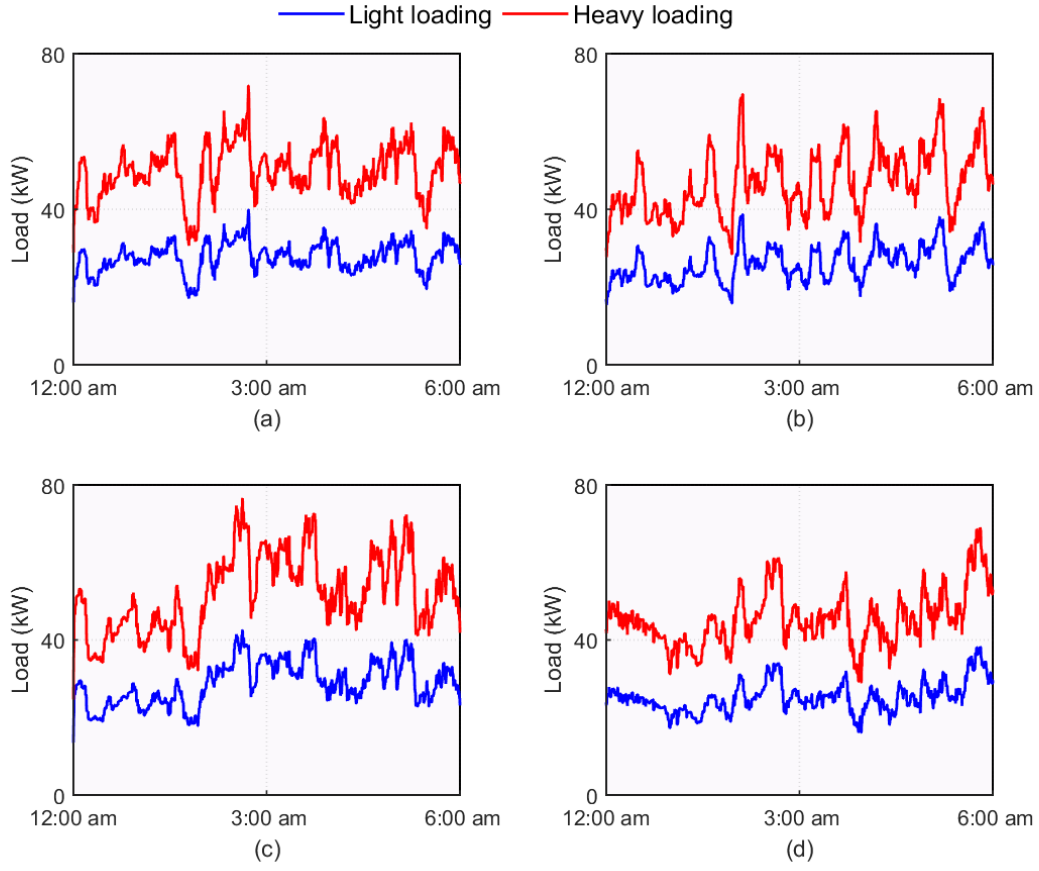


Figure 5.1: Non-TCL load profile during light and heavy loading conditions at: (a) Node-2A (b) Node-2E (c) Node-8A (d) Node-8E.

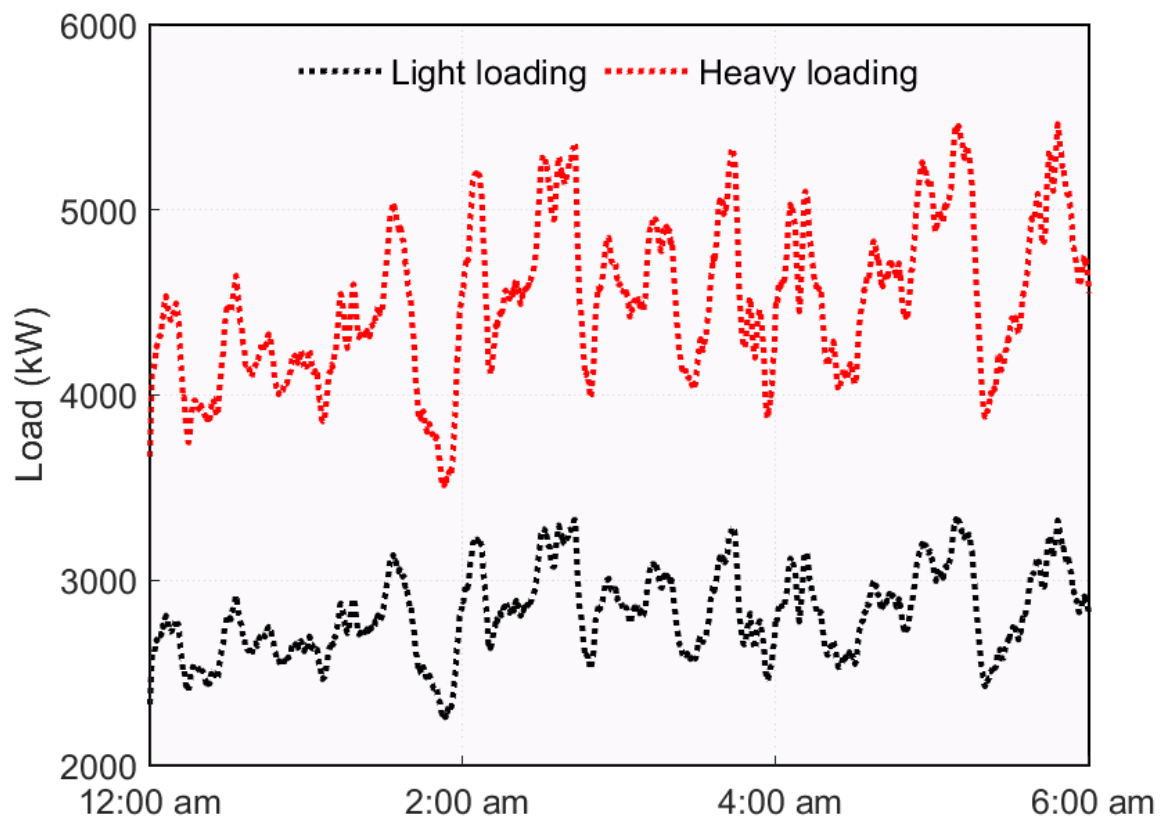


Figure 5.2: Total system light and heavy load profile.

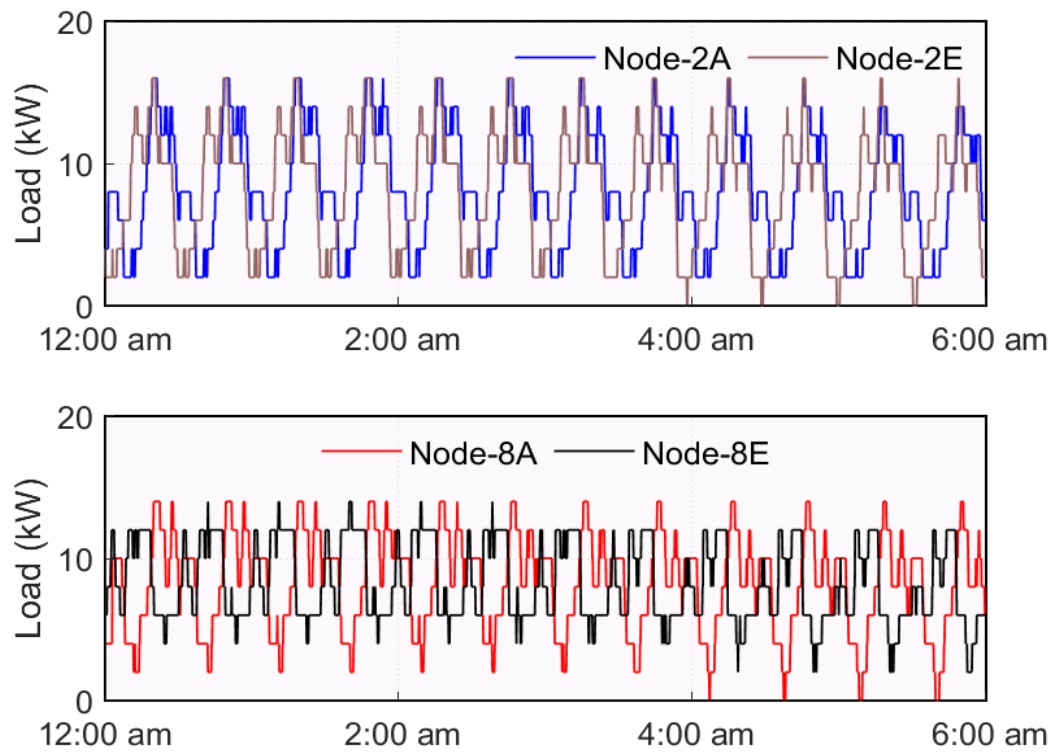


Figure 5.3: TCL load profiles for the base case.

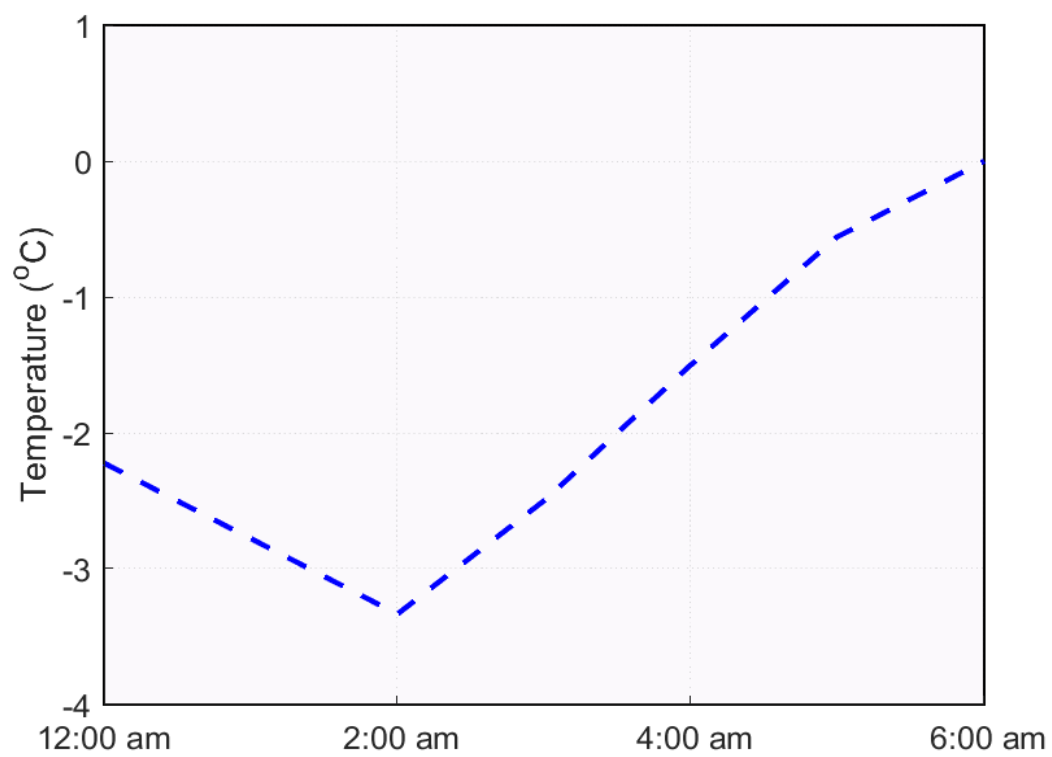


Figure 5.4: Outside temperature in °C.

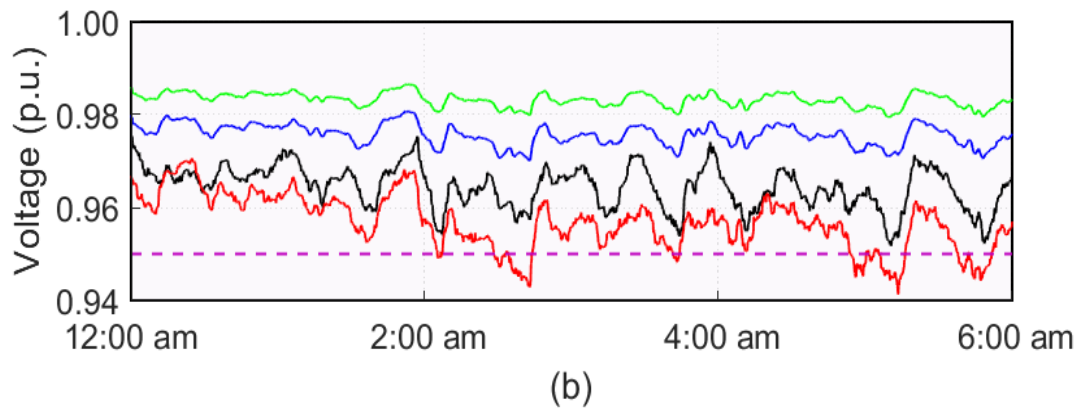
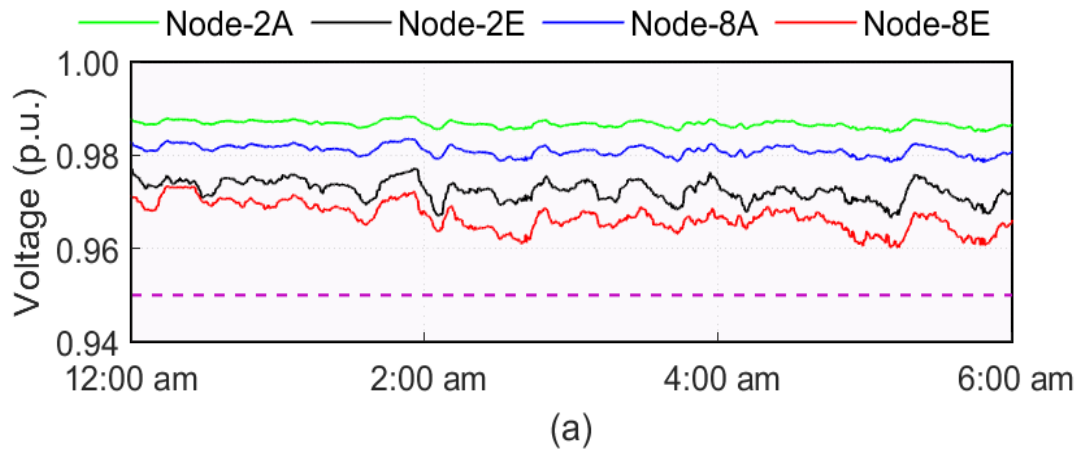


Figure 5.5: Base case voltage profiles during: (a) light loading (b) heavy loading.

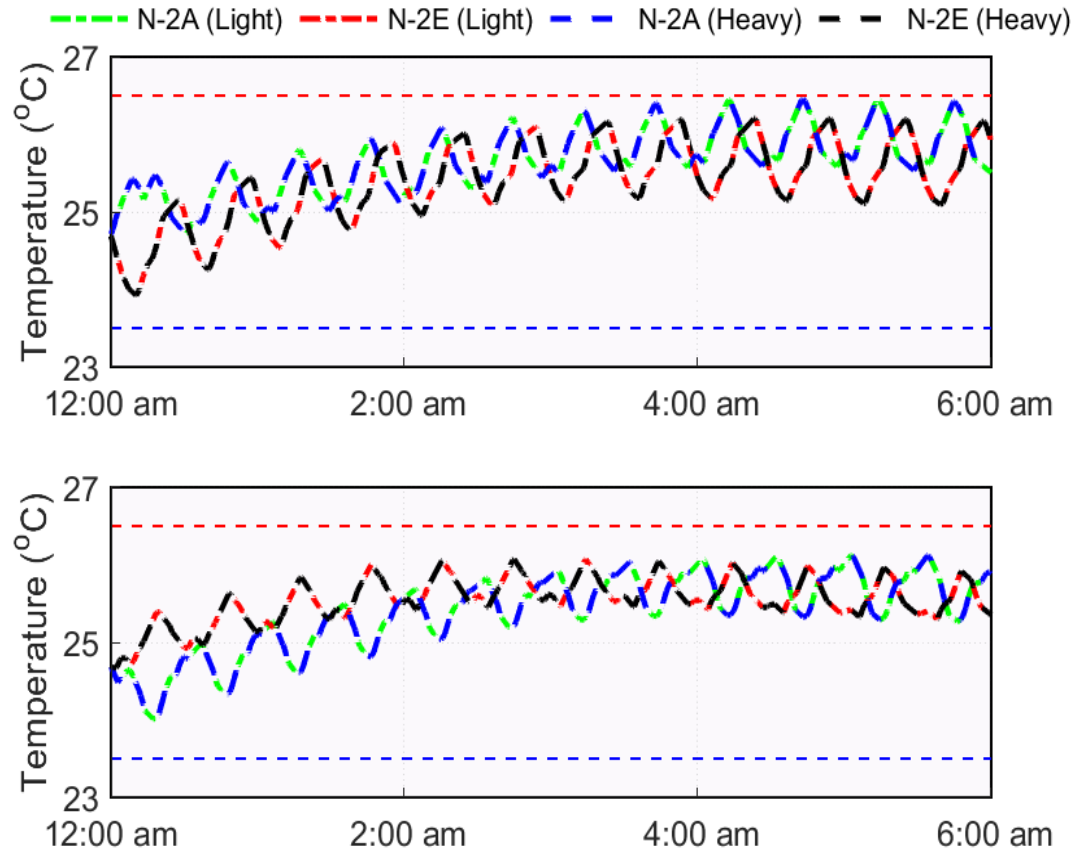


Figure 5.6: Base case temperature profiles for Node-2A, Node-2E, Node-8A, and Node-8E.

Parameter	Value
Voltage Violations	373 Customer.Minutes
Temperature Violations	0 Customer.Minutes
Energy (Light Loading)	16921 kWhr
Energy (Heavy Loading)	27085 kWhr

Table 5.1: Base Case Energy Consumption, Voltage, and Temperature Violations.

5.1.1 Sensitivity

The actual sensitivities obtained from the DIgSILENT PowerFactory are compared with the sensitivities estimated from the proposed algorithm in [2] during the light and heavy loading conditions. The continuous small perturbations in online sensitivities around the actual sensitivity curve captures important randomness in data for machine learning through NNs. Fig. 5.8 and 5.7, show the results for online sensitivities estimation plotted along with the Jacobian Matrix sensitivities calculated in DIgSILENT PowerFactory.

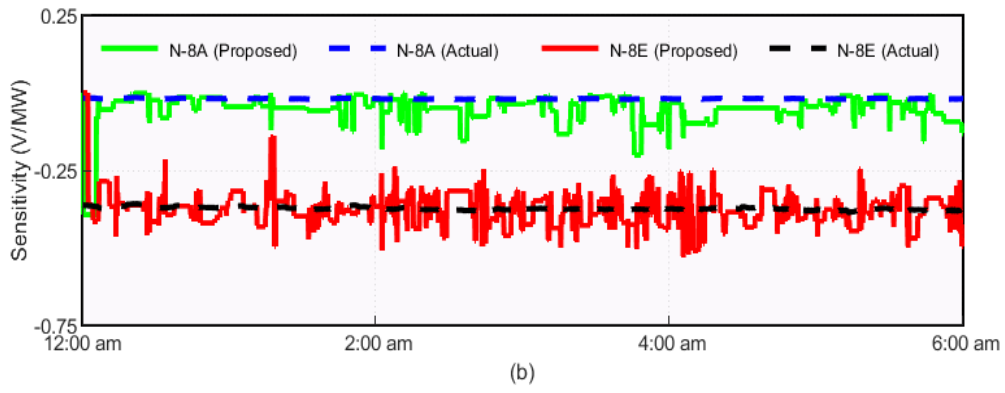
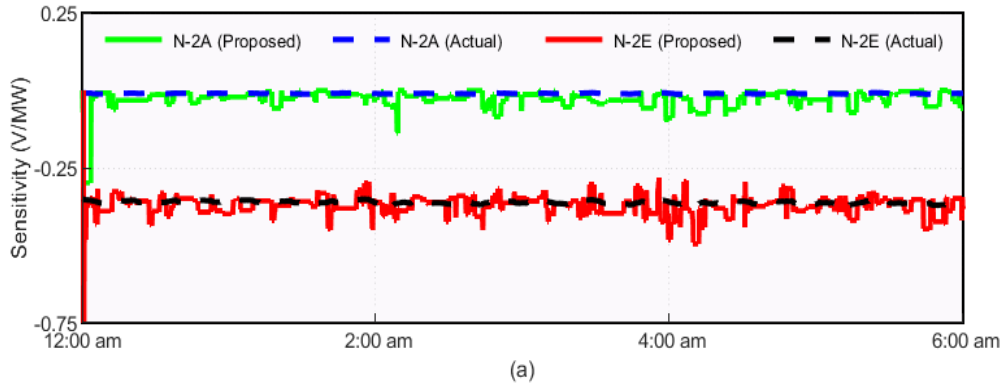


Figure 5.7: DlgSILENT online sensitivity estimation plot for heavy loading system state.

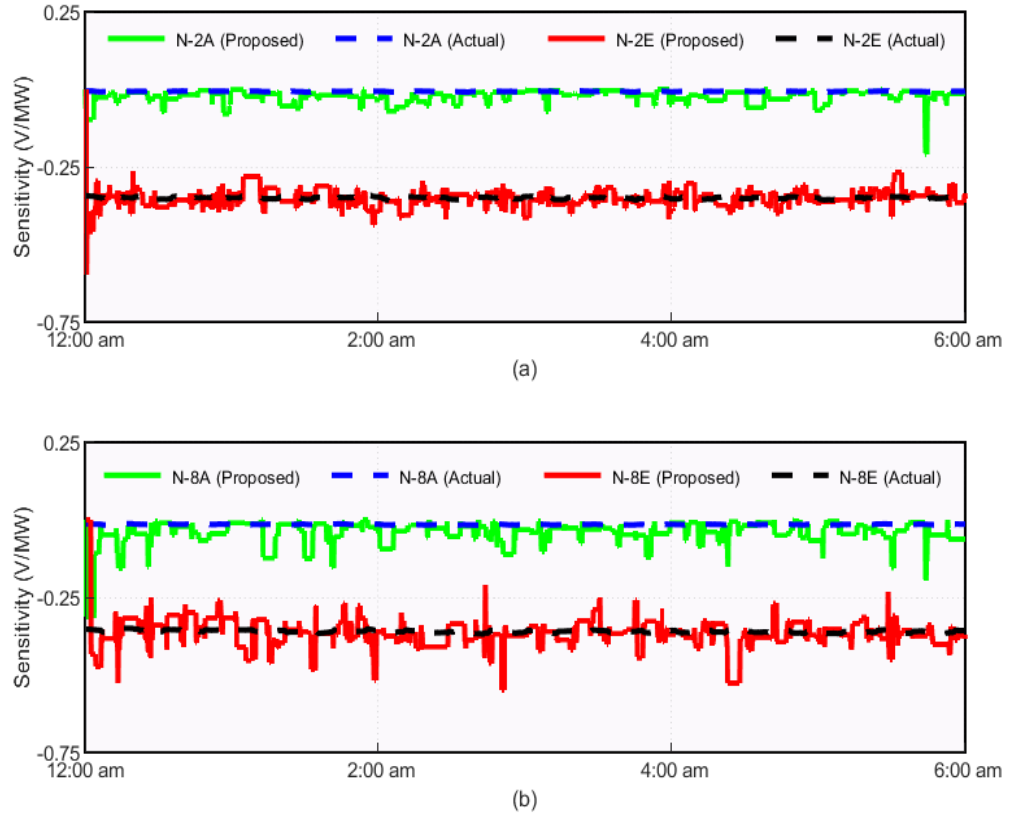
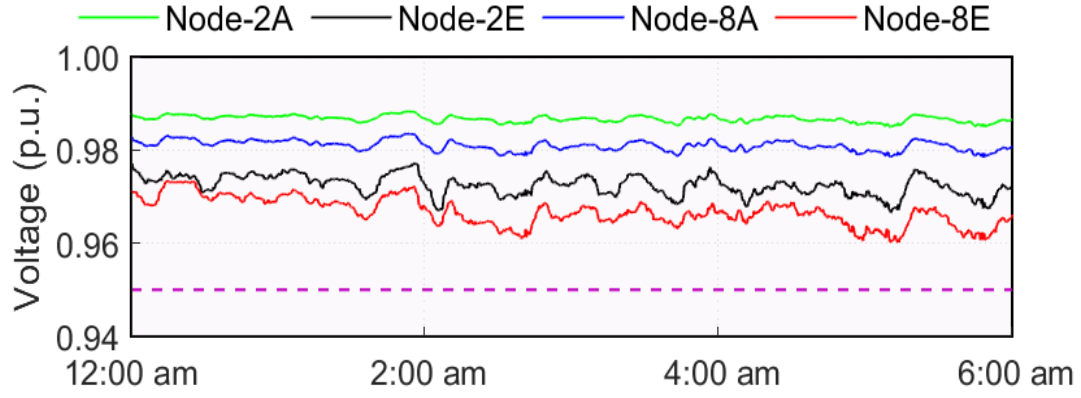


Figure 5.8: Voltage-to-load sensitivities during light loading condition.

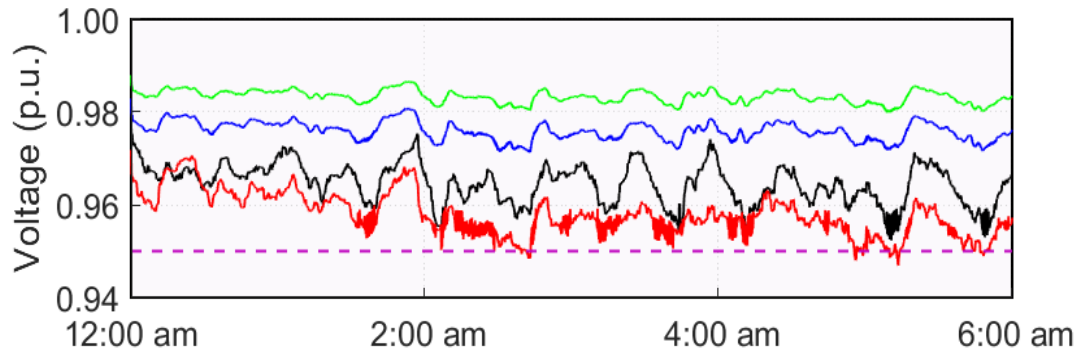
5.2 A Simple on/off-Based TCLs Controller

As mentioned earlier that there are voltage violations in the base system case, i.e., without any TCLs controller in the system thus, a simple on/off TCL controller is implemented. The on/off TCL-based controller implements a simple strategy of turning the TCLs on and off responding to the system voltage violations. The TCLs will operate as per the temperature settings and whenever there are voltage violations in the system the TCLs will be turned off. The setpoint temperature is set as 25°C and a temperature dead-band is set to $\pm 1.5^{\circ}\text{C}$ to implement the simple TCLs controller. As there are no voltage violations during the light loading case so the TCLs are turned on and off by responding to the temperature setpoint of 25°C and the temperature stays within the specified bounds of $\pm 1.5^{\circ}\text{C}$ around the set point. During heavy loading condition there are considerable voltage violations and the on/off TCL controller shows significant improvements in the voltage profiles of the system nodes as shown in Fig. 5.9. However, this type of controller results in temperature violations. The customers' temperature settings are ignored by the simple on/off-based control strategy as outlined in Fig. 5.10. The TCL profiles for the on/off-based strategy are shown in Fig. 5.11. Observations from the TCL plot in Fig. 5.11, illustrate that the TCLs connected at the downstream nodes are always at a disadvantage due to the location of these nodes as they are frequently turned off responding to the voltage violations at these nodes.

The simple on/off control strategy address the issue of voltage violations in the system but it cannot maintain the customers' temperature profile i.e., customers' comfort is sacrificed while mitigating the system voltage violations. The customers' temperature violations exist for a period of 21630 customer seconds, i.e., the temperature violations exist all the time in the system. The violation indices and energy consumption profile of the system for the On/Off controller are given in Table 5.3.



(a)



(b)

Figure 5.9: Voltage Profiles of the Nodes with on/off-Based TCLs during: (a) light loading (b) heavy loading condition.

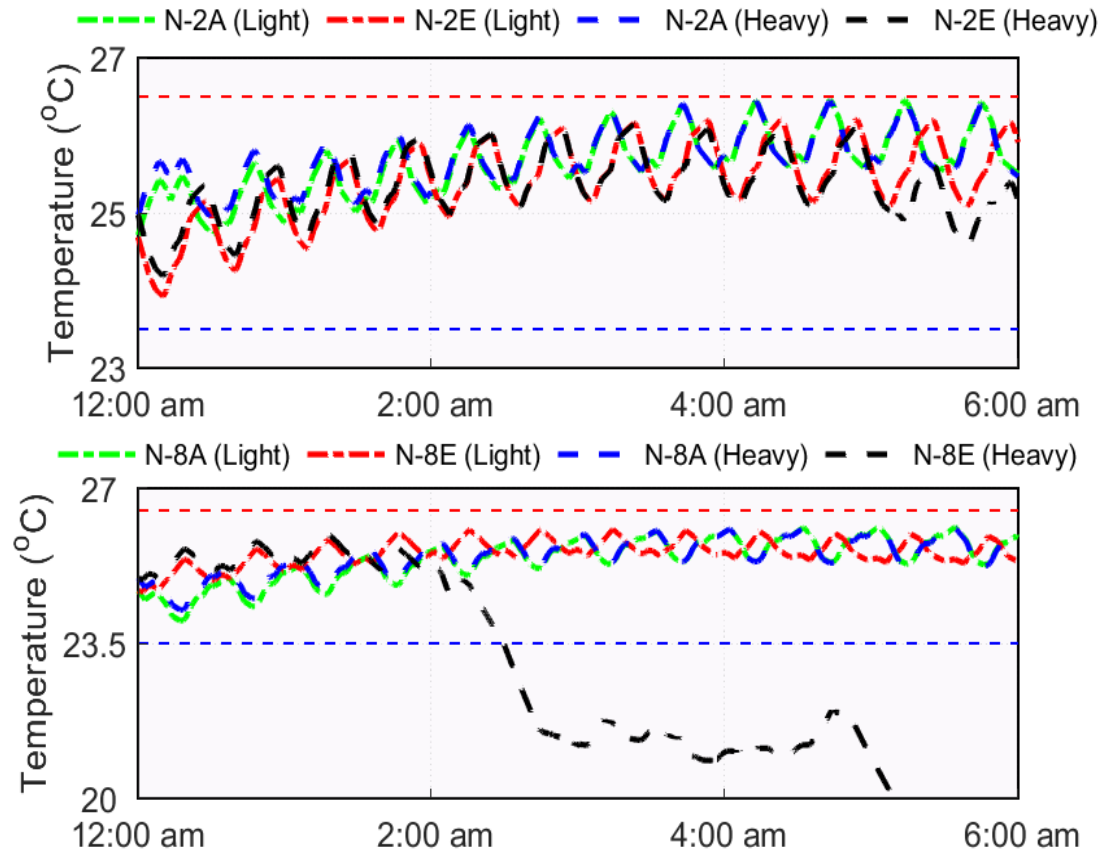


Figure 5.10: Temperature profiles with on/off-based TCL controller during light and heavy loading conditions.

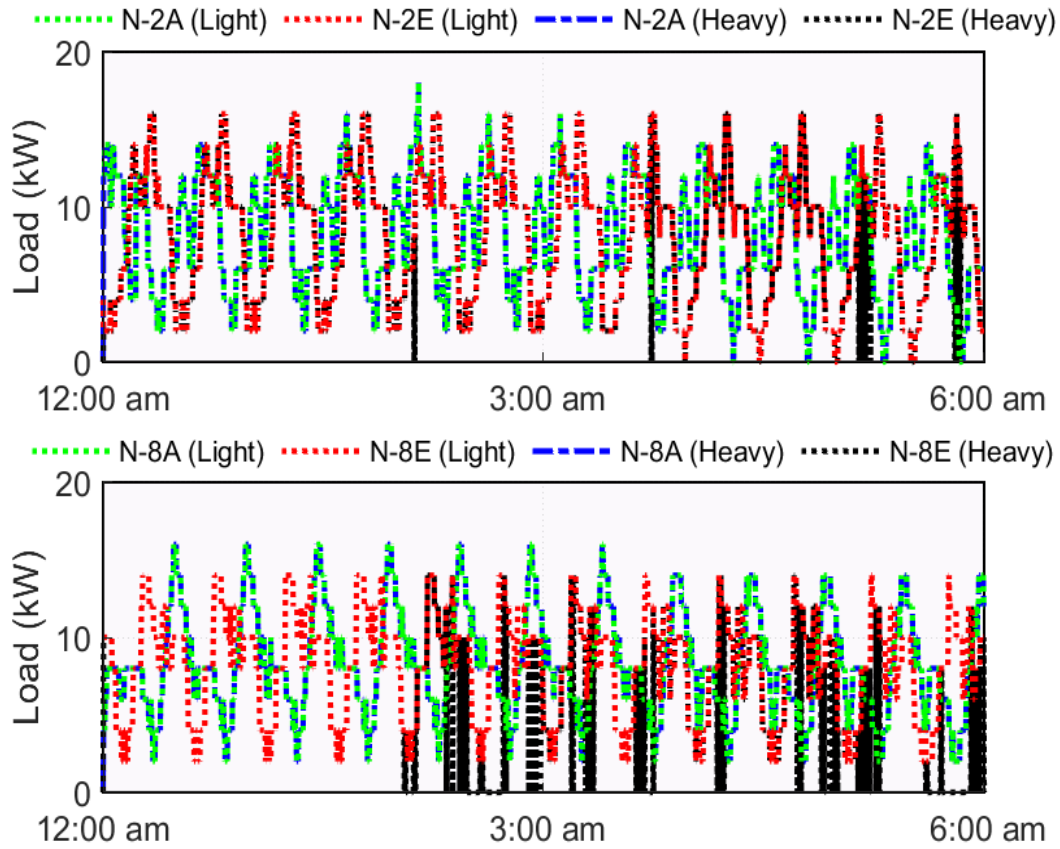


Figure 5.11: TCL profiles with on/off-based TCL controller during light and heavy loading conditions.

Parameter	Value
Voltage Violations	61.5 Customer.Minutes
Temperature Violations	26130 Customer.Minutes
Energy (Light Loading)	16921 kWhr
Energy (Heavy Loading)	26905 kWhr

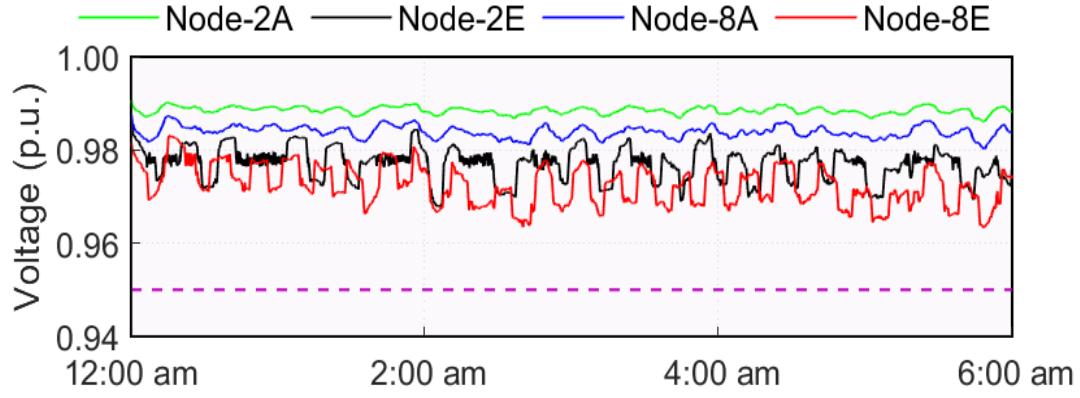
Table 5.2: Simple On/Off Controller's Voltage, Temperature Violations, and Total Energy Consumption.

5.3 Proposed Voltage-and Sensitivities-Based DR controller

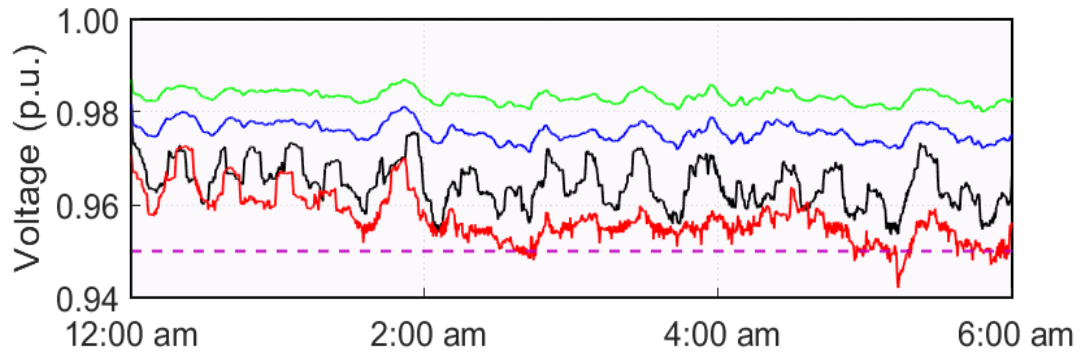
To compare and evaluate the ML-based DR controller in terms of control actions for the TCLs, the same specific nodes (i.e. Node-2A, Node-2E, Node-8A, and Node-8E) will be considered. The DR controller successfully manage TCLs and control the end-user's temperature profile within the specified bound of ΔT , which is set to $\pm 1.5^\circ\text{C}$ around the setpoint of T_s , set to 25°C . The proposed controller improves the voltage profile, shown in Fig. 5.12, as compared to the base heavy loading case in which the voltage violations exist for an extended period. The voltage violations are reduced to 106.7 customer minutes as compared to the base case voltage violations of 373 customer minutes. The temperature profiles maintained by the proposed controller are shown in Fig. 5.14.

The controller keeps track of the end-user's temperature and system voltage. When a violation occurs in the system it curtails the TCL while maintaining the temperature profile of the end-user within the specified bounds. By the integration of machine learning, the proposed scheme controls multiple SH loads located at different nodes in the distribution system as illustrated in Fig. 5.13. During the system light loading condition temperatures are closer to the upper bound T_{max} (26.5°C) and hence, the TCL states remain either β_o or β_M . On the other hand, the status of the TCL at the downstream nodes become β_L for a while during the system heavy loading condition

to respond to the voltage violations at these nodes as demonstrated in the controller strategy in section 3.3.1. The voltage violations, temperature violations, and energy consumption indices for the DR controller are given in Table 5.3.



(a)



(b)

Figure 5.12: Voltage profiles with the proposed controller during: (a) light loading condition (b) heavy loading condition.

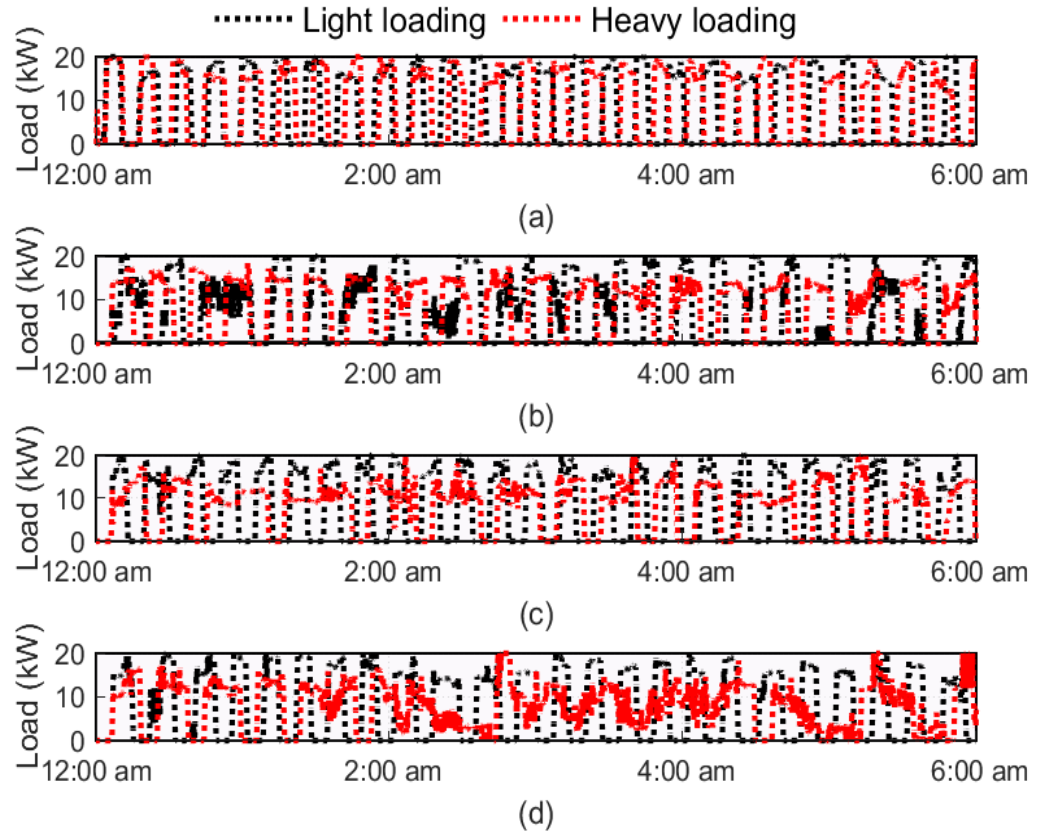


Figure 5.13: TCL profiles with the proposed controller at (a) Node-2A (b) Node-2E (c) Node-8A (d) Node-8E.

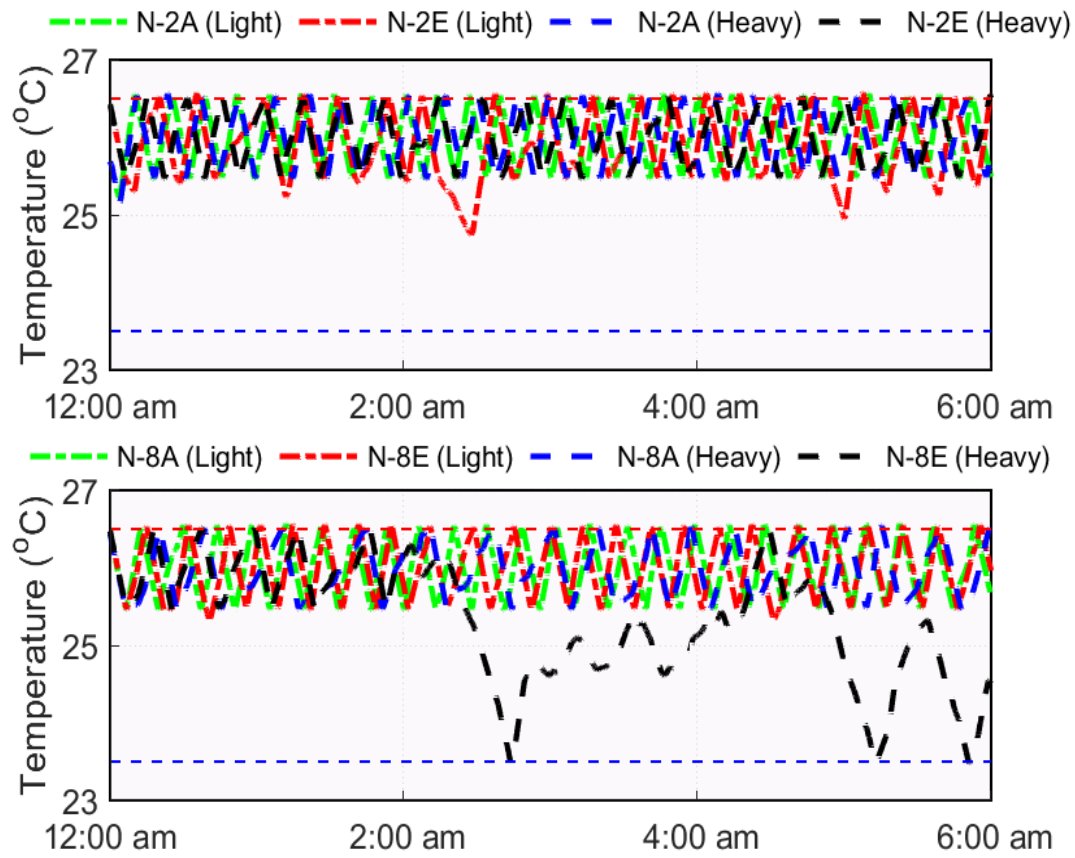


Figure 5.14: Temperature profiles with the proposed controller.

Index	Value
Voltage Violations	106.7 Customer.Minutes
Temperature Violations	0 Customer.Minutes
Energy (Light Loading)	16837 kWhr
Energy (Heavy Loading)	27006 kWhr

Table 5.3: Proposed Controller's Voltage, Temperature and Energy Indices.

5.3.1 System Reconfiguration Impact

To further assess the efficacy of the proposed control framework a reconfiguration in the distribution system's architecture has been made. An upstream node in the system has been disconnected from its upstream location, i.e., Node 18 has been disconnected from the upstream feeding path from Node 16 and connected to the downstream Node 12. The simulation demonstrates improved results even after network re-structuring. The DR controller improves the voltage profiles and maintain users' comfort in terms of the temperature profiles. From the indices in Table 5.4, the voltage violations for the system reconfiguration case are reduced to 106 customer minutes. System reconfiguration did not affect the DR controller's strategy as the customers' temperature profiles remain within the specified temperature bounds as shown in the temperature plot in 5.17. The voltage and TCLs profile for the Node-2A, Node-2E, Node-8A, and Node-8E are given in Figs. 5.15 and 5.16.

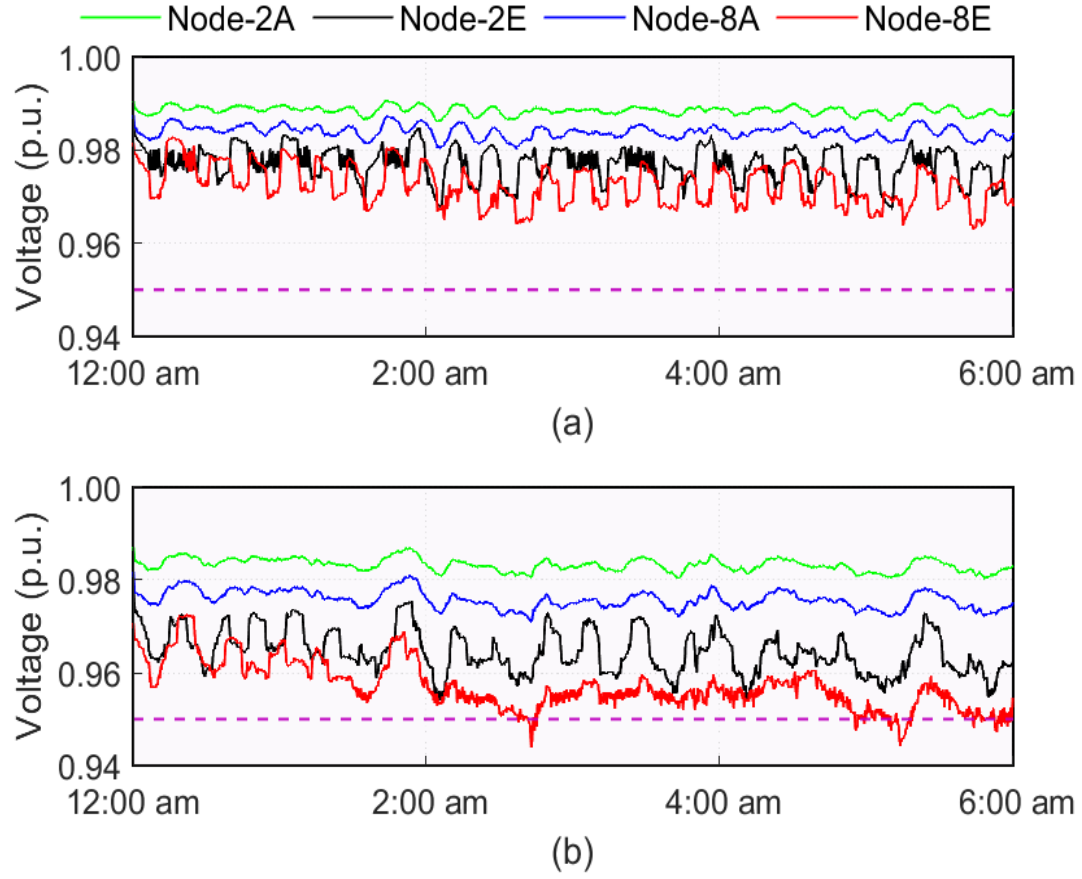


Figure 5.15: Voltage profiles with the proposed controller under system reconfiguration during (a) light loading condition (b) heavy loading condition.

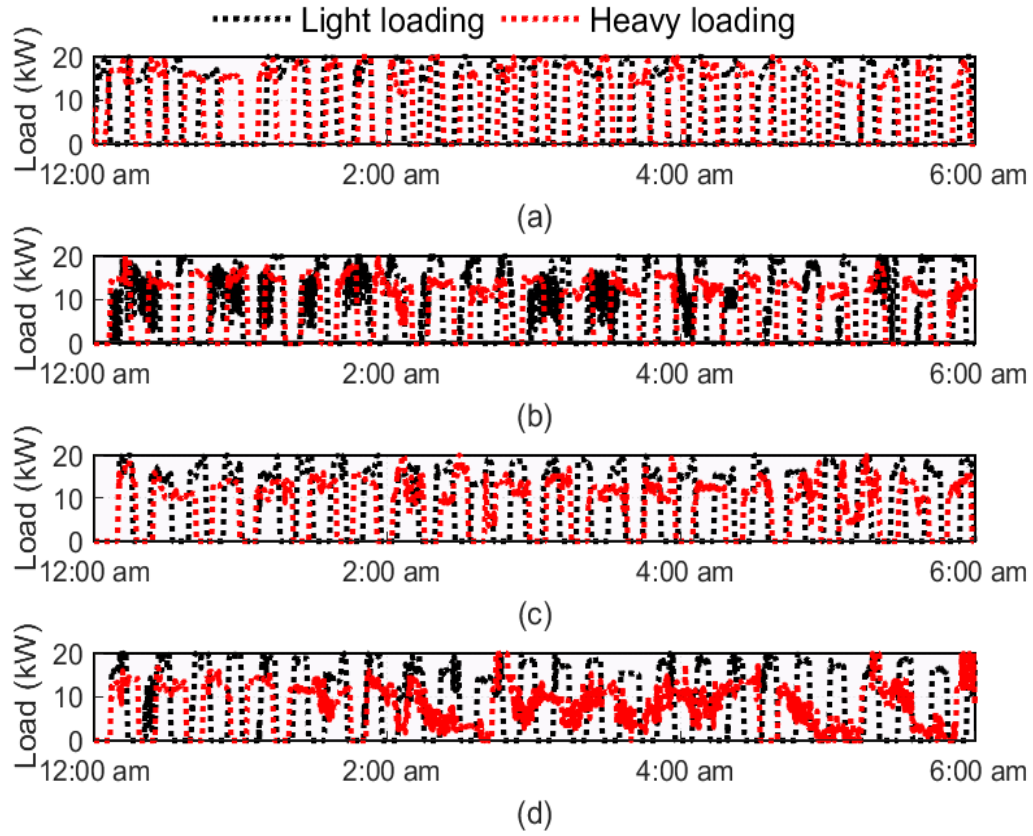


Figure 5.16: TCL profiles with the proposed controller under system reconfiguration at: (a) Node-2A (b) Node-2E (c) Node-8a (d) Node-8E.

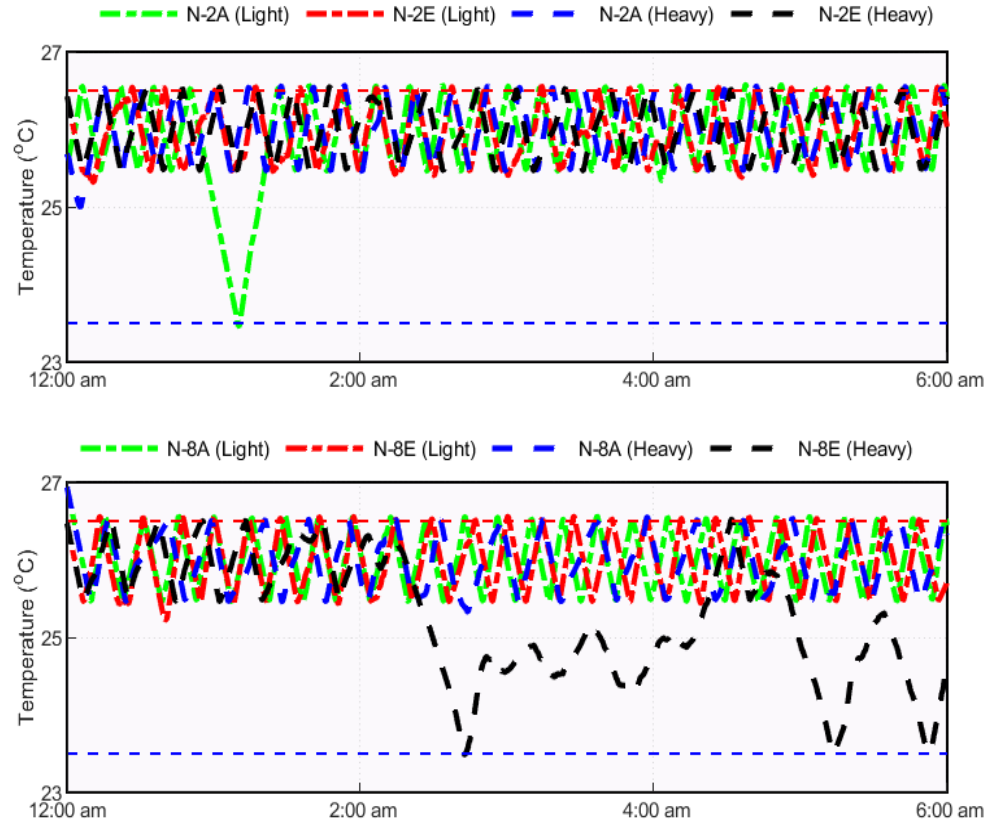


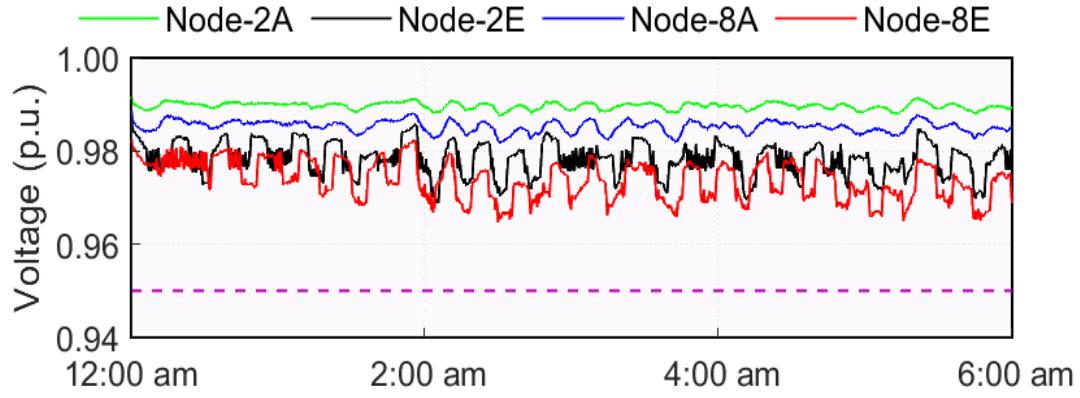
Figure 5.17: Temperature profiles with the proposed controller under system reconfiguration.

Index	Value
Voltage Violations	106 Customer.Minutes
Temperature Violations	0 Customer.Minutes
Energy (Light Loading)	16868 kWhr
Energy (Heavy Loading)	27002 kWhr

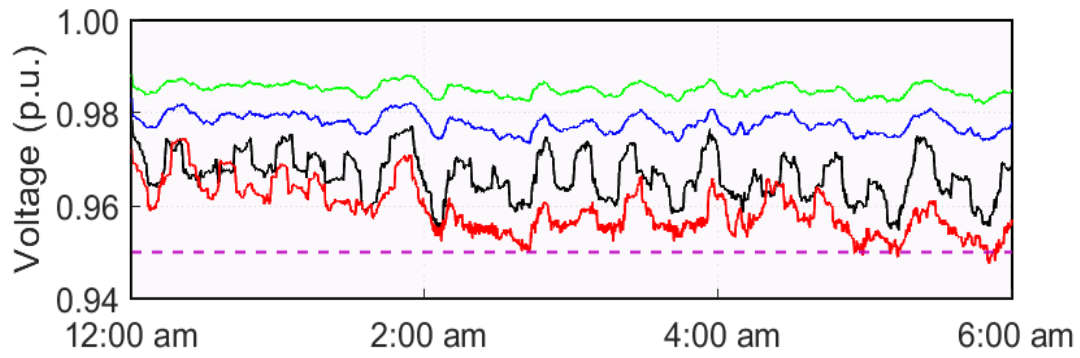
Table 5.4: Controller's Voltage, Temperature And Energy Indices For The System Reconfiguration Case.

5.3.2 Inclusion of Shunt Capacitors

A Shunt capacitor (SC) is connected at Node-5A in the distribution system to rate the usefulness of the control approach with the integration of a voltage control device. The maximum reactance provision from the SC has been limited to 1 MVar. Results demonstrate that the controller can still effectively work in ensuring customers' comfort and the voltages are improved pronouncedly this time as SC aid the purpose the voltage profile improvements. The voltages, TCLs profile, and temperature profiles for SC inclusion case for Node-2A, Node-2E, Node-8A and Node-8E are shown in Figs. 5.18, Fig. 5.19, and Fig. 5.20 respectively. It can be noticed that the temperature profiles are significantly improved in general, and for Node-8E in particular since the voltages have been improved due to the inclusion of a SC. The voltage violations are further reduced to 10.7 customer minutes as compared to the proposed case voltage violations of 107 customer minutes. The controller's indices for the shunt capacitor inclusion case are given in Table 5.5.



(a)



(b)

Figure 5.18: Voltage profiles for Node-2A, 2E and Node-8A, 8E for SC inclusion case during heavy loading.

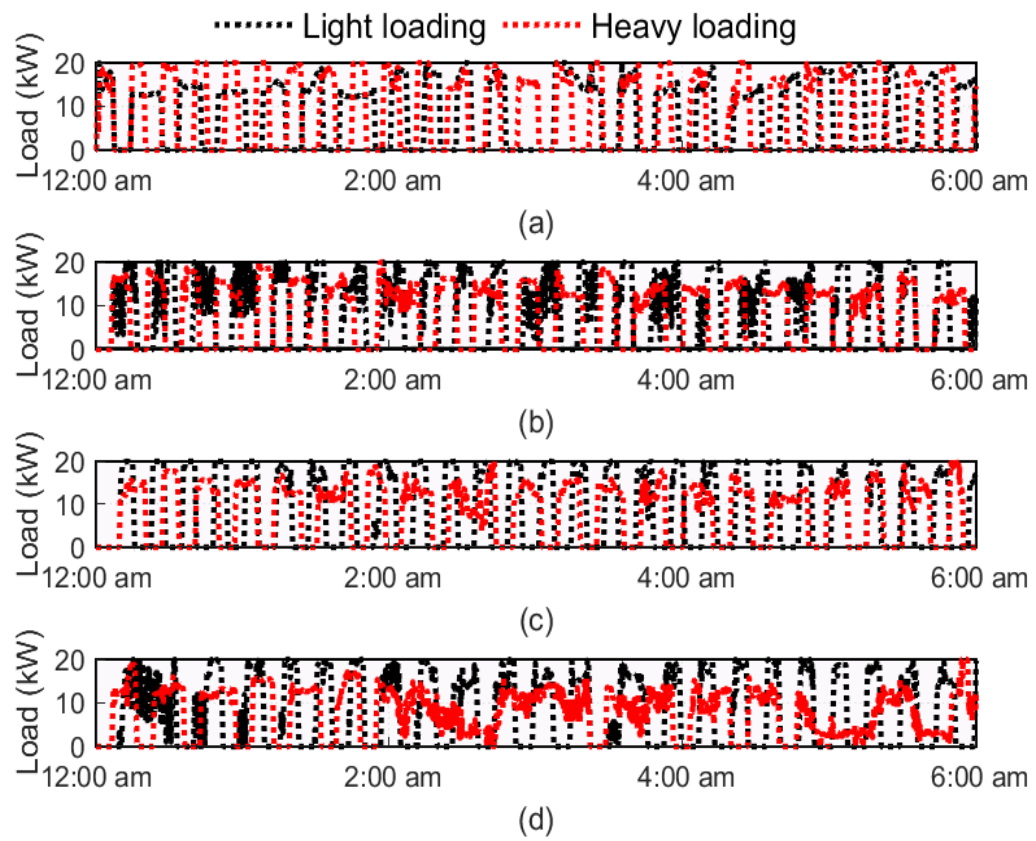


Figure 5.19: TCLs profiles for Node-2A, 2E and Node-8A, 8E.

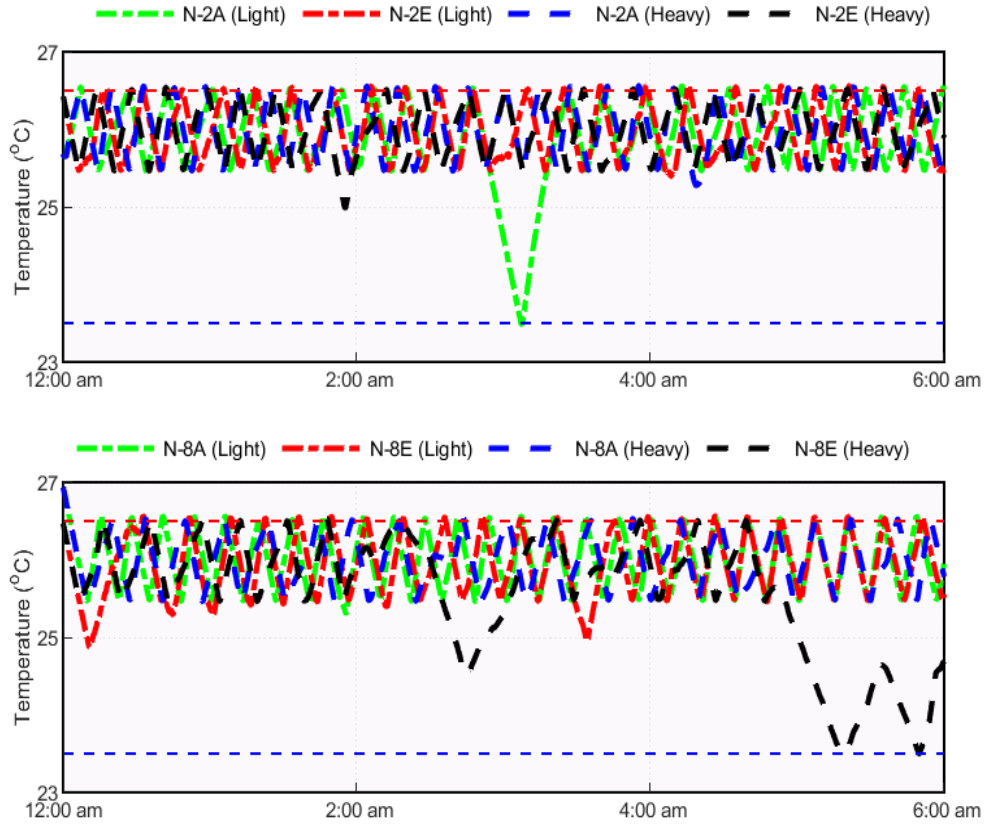


Figure 5.20: Temperature profiles for Node-2A, 2E and Node-8A, 8E heavy system loading case.

Index	Value
Voltage Violations	10.7 Customer.Minutes
Temperature Violations	0 Customer.Minutes
Energy (Light Loading)	16852 kWhr
Energy (Heavy Loading)	27013 kWhr

Table 5.5: Controller's Voltage, Temperature And Energy Indices For The Shunt Capacitor Inclusion Case.

5.3.3 Inclusion of Distributed Generator

Distributed generation such as wind is becoming ubiquitous, thus, it is important to evaluate the proposed DR controller's performance during a DG integration. A wind DG with a rated capacity of 20 kW is integrated with the Node-8E of the secondary distribution system. The power output profile, shown in Fig. 5.21, for the wind generator is adopted from the Bonneville Power Administration reference in [87]. It can be noticed that the proposed controller significantly diminishes voltage violations and maintain temperatures among the nodes independently of their spots in the secondary system. The improved voltage profiles are shown in Figs. 5.22. The TCL profiles and the selected node profiles are plotted in Fig. 5.23 and Fig. 5.24. It can be observed that the voltage profiles are significantly improved for all the nodes as the voltage violations exist only for 99 customer minutes. The voltage, temperature, and energy indices are given in Table 5.6.

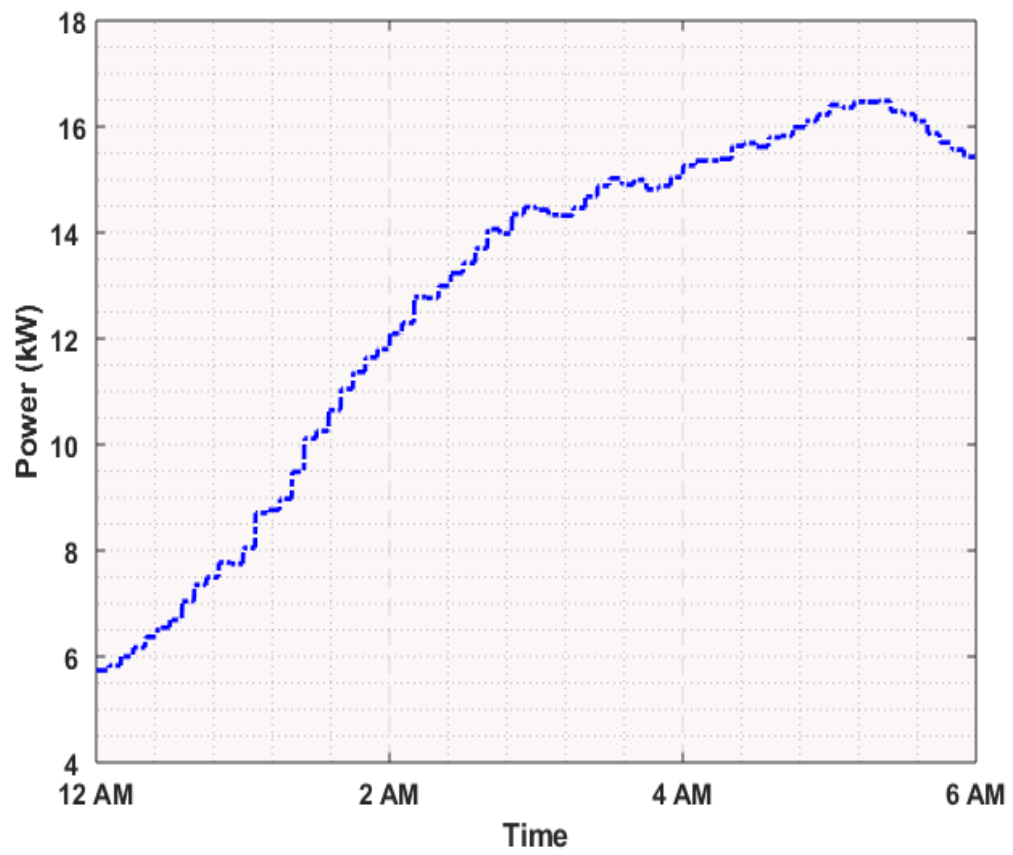


Figure 5.21: DG output power profile.

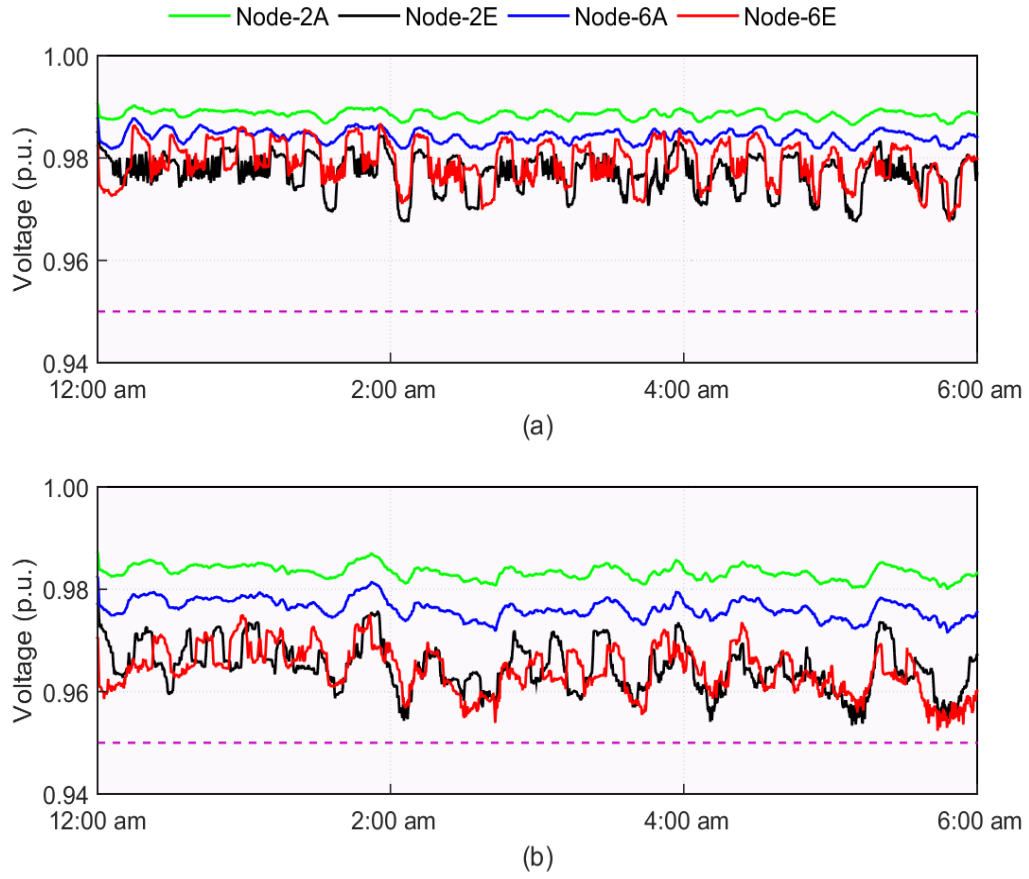


Figure 5.22: Voltage profiles with the proposed controller with DG integration during: (a) light loading condition (b) heavy loading condition.

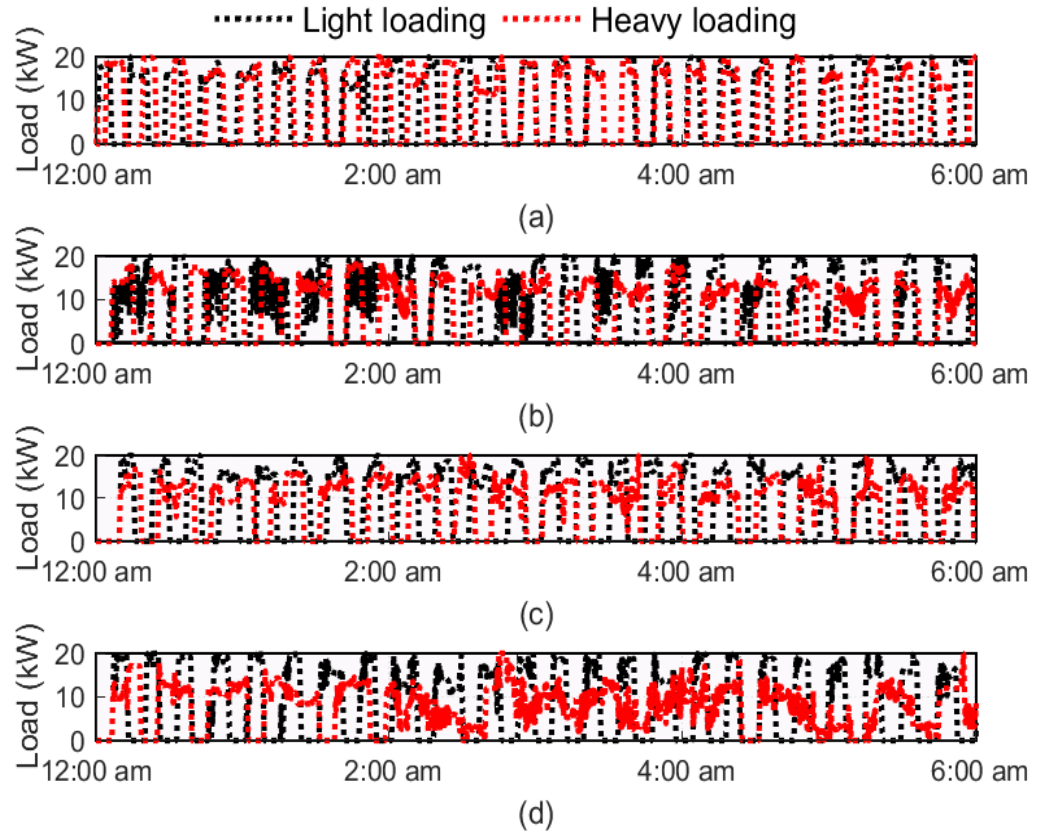


Figure 5.23: TCL profiles with the proposed controller at (a) Node-2A (b) Node-2E (c) Node-8A (d) Node-8E with the DG.

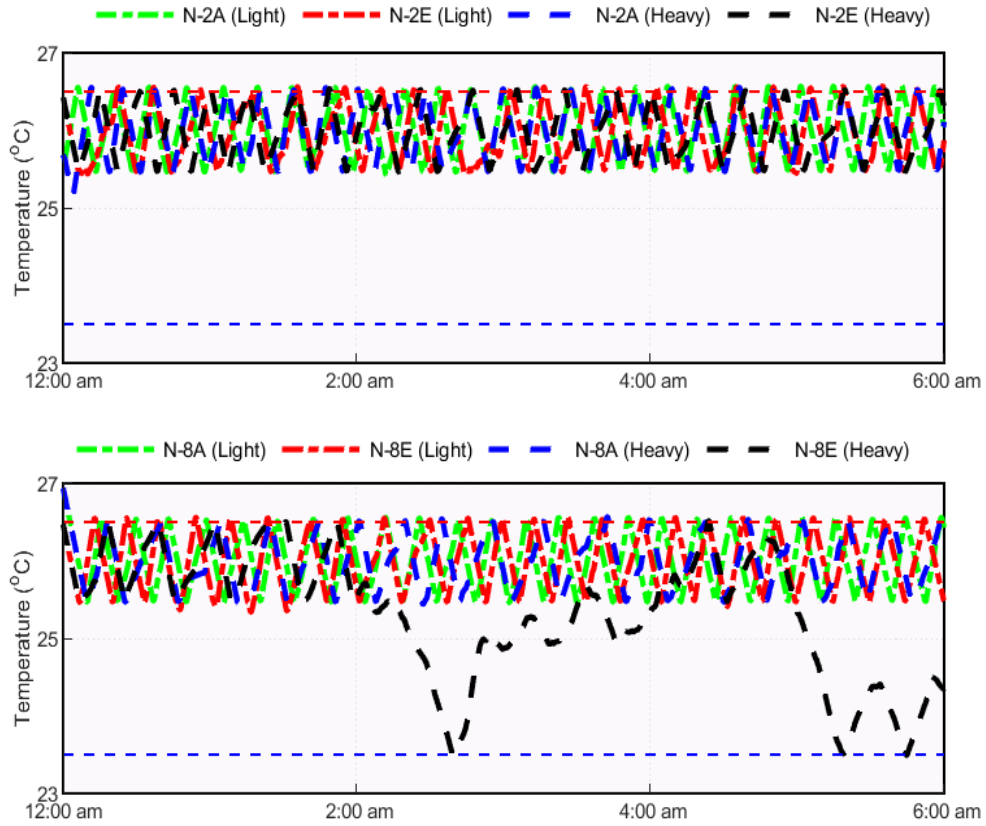


Figure 5.24: Temperature profiles with the proposed controller under the inclusion of DG.

Index	Value
Voltage Violations	99.6 Customer.Minutes
Temperature Violations	0 Customer.Minutes
Energy (Light Loading)	16856 kWhr
Energy (Heavy Loading)	27010 kWhr

Table 5.6: Controller's Voltage, Temperature and Energy Indices For The Inclusion of a Wind DG.

5.4 Test Under A Different Ambient Temperature Profile

The DR controller is tested under a different ambient temperature profile that is shown in Fig. 5.25. To compare and evaluate the DR controller in terms of control actions for the TCLs, the same specific nodes (i.e. Node-2A, Node-2E, Node-8A, and Node-8E) are considered. The DR controller successfully manage the TCLs even during a different outside ambient temperature profile. The controller controls the end-user's temperature profile within the specified bounds of $\pm 1.5^{\circ}\text{C}$ around the setpoint of 25°C . The proposed controller improves the voltage profile as shown in Fig. 5.26. From the Table 5.7, the voltage violations are reduced to 47.6 customer minutes. The temperature profile maintained by the proposed controller is shown in Fig. 5.28. The TCLs profile for specific nodes are shown in Fig. 5.27.

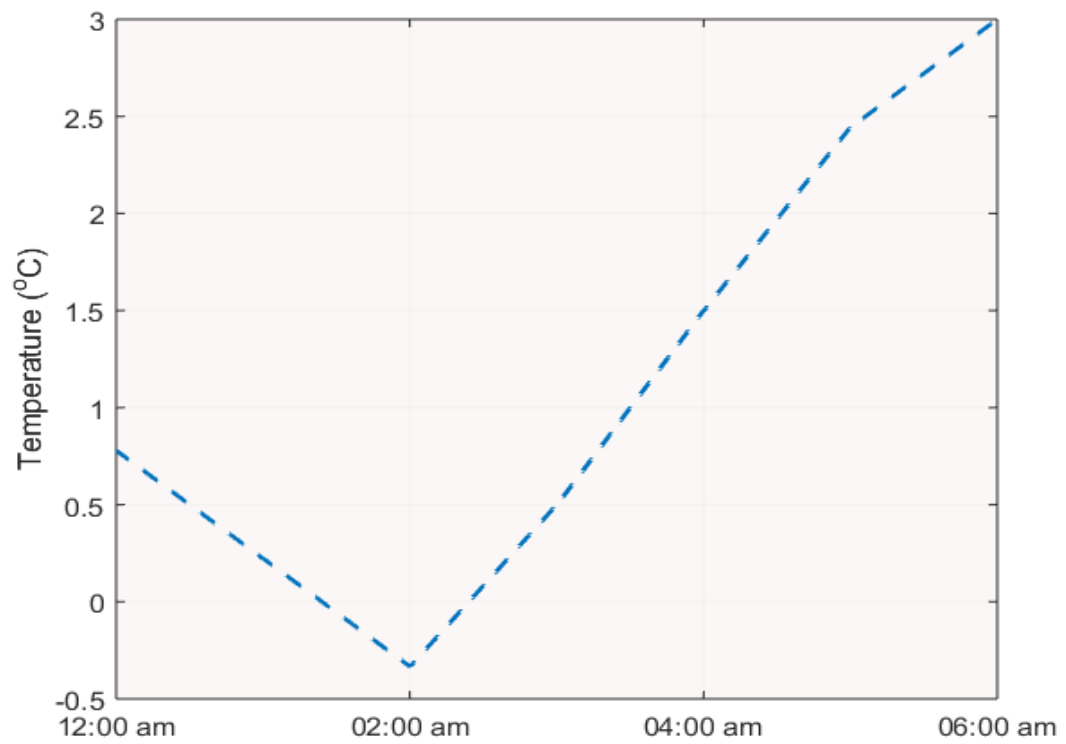
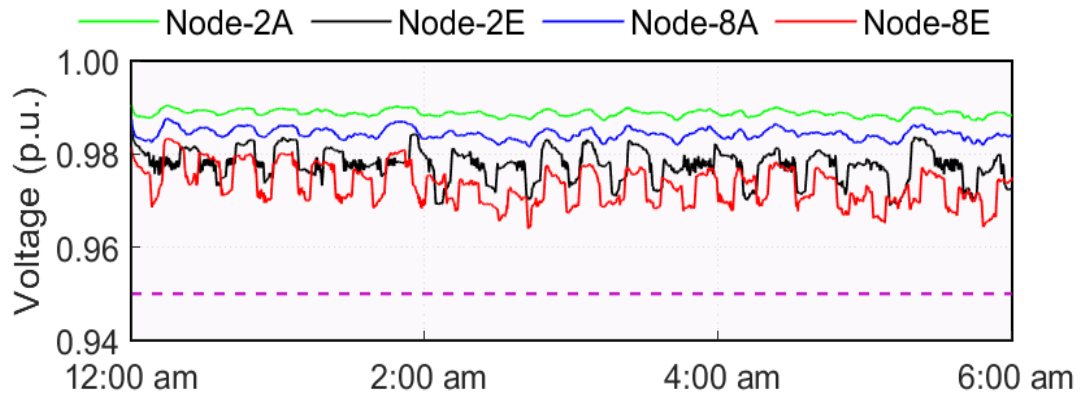
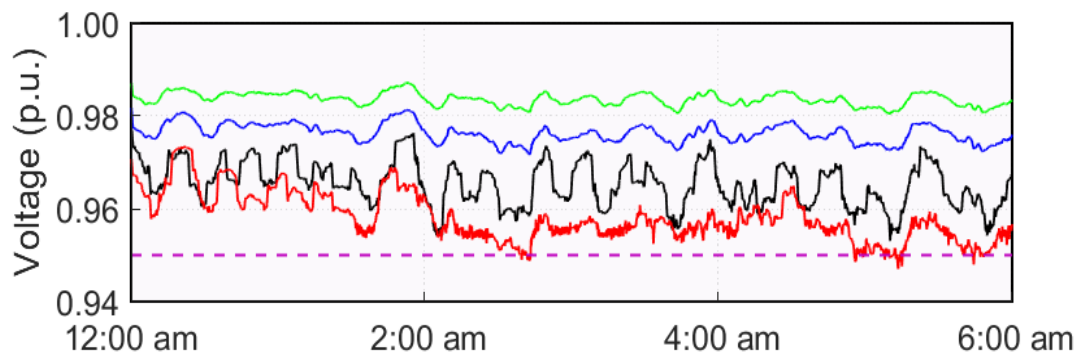


Figure 5.25: A different ambient temperature profile in °C.



(a)



(b)

Figure 5.26: Voltage profiles during: (a) light loading condition (b) heavy loading condition.

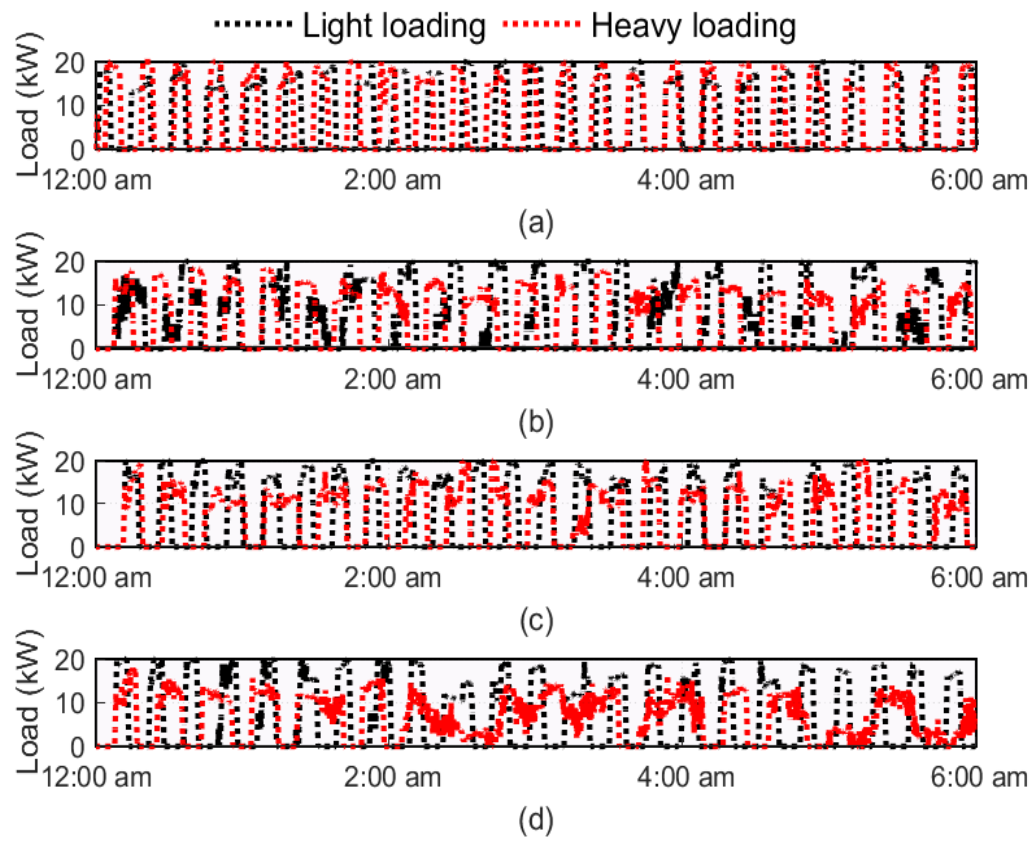


Figure 5.27: TCL profiles at (a) Node-2A (b) Node-2E (c) Node-8A (d) Node-8E.

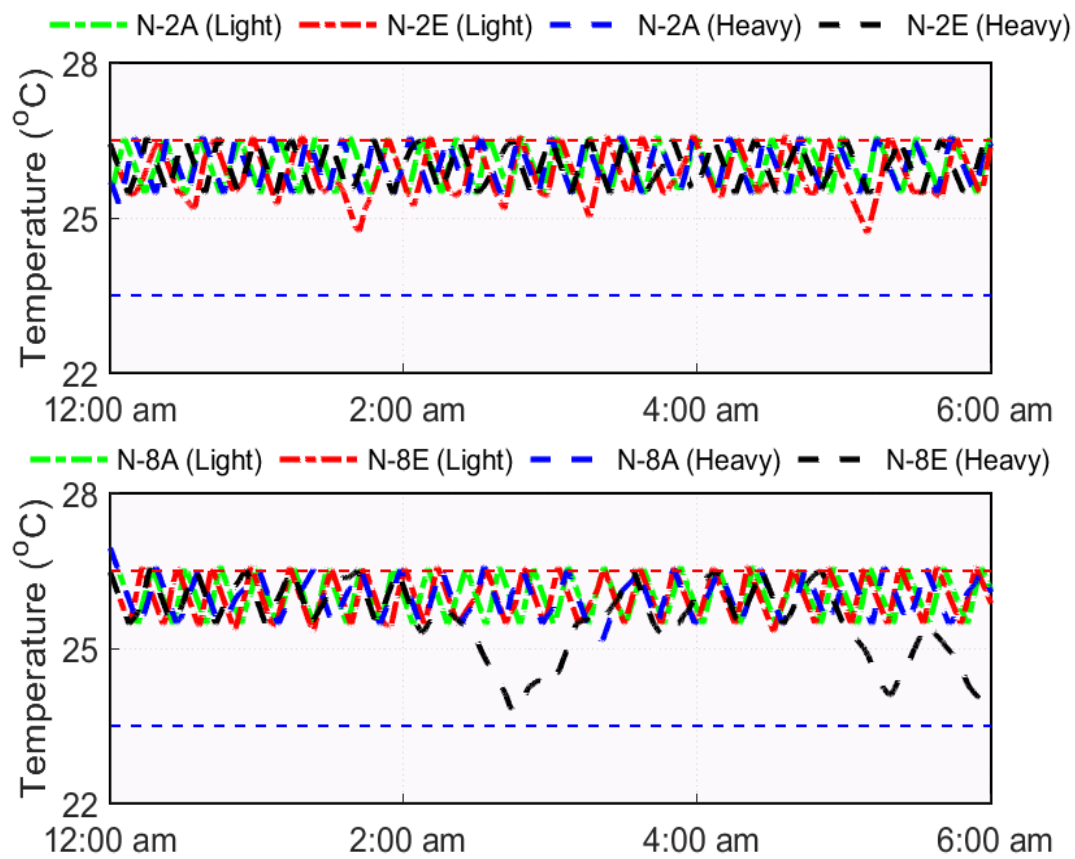


Figure 5.28: Temperature profiles.

Index	Value
Voltage Violations	47.6 Customer.Minutes
Temperature Violations	0 Customer.Minutes
Energy (Light Loading)	16212 kWhr
Energy (Heavy Loading)	26378 kWhr

Table 5.7: Proposed Controller's Voltage, Temperature and Energy Indices For a Different Ambient Temperature.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this thesis, an online estimation concept for the voltage-to-load sensitivity is utilized in designing an autonomous machine learning (ML)-based demand response (DR) controller that incorporates thermostatically controlled loads (TCLs). The controller parameters are derived from training a fully connected Multi-Layer Perceptron (MLP) neural network. The controller applies maximum TCL power caps in proportion to the system conditions without the need for communication. The system voltage violations are also mitigated by the simple on/off-based controllers discussed in section 5.2, but it unjustifiably violates temperature profiles and hence customers' comfort. Control strategy simulations in DIgSILENT and MATLAB successfully demonstrate remarkable improvements in voltage profile and users' comfort through conveniently maintaining end-user's temperature profile. Thus, the important services of voltage

regulation within the acceptable range as defined by ANSI C84.1-2016 standards and better utilization of the TCLs are adequately met. As the proposed controller is autonomous and no remote monitoring is required thus, the local measurements of voltage and its sensitivity serve as inputs to the controller for determining the maximum power caps. The controller is trained on different loading conditions to incorporate the daily, monthly, and yearly load variations.

The proposed controller performs well even during system reconfiguration. Also, the controller shows remarkable results in the presence of wind DG. The performance of the proposed controller is further assessed when a voltage control device such as Shunt Capacitor (SC) is connected in the distribution system and the results demonstrate improved performance. Simulations also affirm the voltage-to-load correlation of the upstream and downstream nodes and the controller employs these characteristics. Thus, the fact that sensitivities can be representative of the system node locations, irrespective of the network topology, is validated.

6.2 Future Work

The control strategy can be extended further for the inclusion of non-TCLs that can be useful in serving the purpose of Demand Side Management (DSM). Important end-user demands that can be aggregated along with the TCLs are the loads that can be delayed and are termed as shift-able loads such as washing machines, tumble dryers, and electric vehicles (EVs). Such loads can provide more flexibility to the DR controller. Thus, further simulations can be carried out to effectively integrate

shift-able demands with curtail-able and non-controllable loads and can enhance the voltage- and sensitivity-based DR strategy. The service of voltage regulation and better utilization of shift-able and curtail-able loads will result in significant annual savings for the DR aggregators in the distribution systems. Additionally, fairness and satisfaction among the customers will ensure wide-scale acceptance of the proposed DR controller. Also, the idea can be implemented for a communication-free control scheme for DGs such as wind and solar PV. The controller will serve the same purpose of regulating system voltages within the acceptable range as per the ANSI C84.1-2016 standard, additionally ensuring fairness. In this context, fairness means all the DGs will contribute equally when the system support is needed . Extended improvements can be considered regarding the ML approaches and data analytics in fine tuning the controller. Finally, the DR controller can be implemented for important ancillary service of frequency regulation such as Frequency-Controlled Reserves for Normal (FCR-N).

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