ADMM-based Multi-Objective Control Scheme for Mitigating the Impact of High Penetration DER Integration in the Modern Distribution Systems

by

Sadaf RAHIMI FAR

THESIS PRESENTED TO ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
IN PARTIAL FULFILLMENT FOR THE DEGREE OF DOCTOR OF
PHILOSOPHY
Ph.D.

MONTREAL, MAY2, 2023

ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
UNIVERSITÉ DU QUÉBEC

BOARD OF EXAMINERS

THIS THESIS HAS BEEN EVALUATED

BY THE FOLLOWING BOARD OF EXAMINERS

Mr. Ambrish Chandra, Thesis Supervisor
Department of Electrical Engineering, École de Technologie Supérieure

Mr. Innocent Kamwa, Thesis Co-supervisor
Department of Electrical and computer Engineering, Laval University

Mr. Tony Wang, President of the Board of Examiners
Department of Automated Manufacturing Engineering, École de technologie supérieure

Mr. Handy Fortin Blanchette, Member of the jury
Department of Electrical Engineering, École de Technologie Supérieure

Mr. Mamadou Lamine Doumbia, External Evaluator
Department of Electrical Engineering and Computer Engineering, Université du Québec à Trois-Rivières

THIS THESIS WAS PRESENTED AND DEFENDED

IN THE PRESENCE OF A BOARD OF EXAMINERS AND PUBLIC

APRIL 13, 2023

AT ÉCOLE DE TECHNOLOGIE SUPÉRIEURE

ACKNOWLEDGMENT

I would like to express my appreciation to my supervisor, Prof. Ambrish Chandra, whose invaluable expertise and support guided me throughout my research journey. I would also like to thank my co-supervisor, Prof. Innocent Kamwa, for his insightful comments and professional guidance.

I must thank Hydro-Quebec's Research Institute (IREQ) for providing me with the opportunity to complete my internship. I must thank the researchers in IREQ, especially Dr. Ali Moeini, for his valuable support and assistance.

I would like to thank the PhD committee members: Prof. Tony Wang, Prof. Handy Fortin Blanchette and Prof. Mamadou Lamine Doumbia for their valuable time in reviewing the dissertation.

I would like to express my endless gratitude to my dear parents for their unconditional love, and dedication. I am deeply indebted to my parents, who have always been a pillar of support in my life. Finally, my special thanks are extended to my husband, Pouyan, for his love, patience, and inspiring encouragement, which have been my constant source of strength and motivation.

Schéma de contrôle multi-objectifs basé sur MMDA pour atténuer l'impact de l'intégration DER à haute pénétration dans les systèmes de distribution modernes

Sadaf RAHIMI FAR

RÉSUMÉ

L'intégration des sources d'énergie renouvelable dans les réseaux de distribution modernes a introduit des défis pour la régulation de la tension du réseau. Dans ce contexte, la présente étude propose une stratégie de contrôle de tension distribuée à agents multiples qui utilise l'algorithme MDAJPM (méthode de direction alternée jacobienne proximale des multiplicateurs) pour les systèmes de distribution d'énergie avec une forte pénétration de ressources photovoltaïques (PV) coordonnées avec des systèmes de stockage d'énergie par batteries (SSEB). L'étude vise à résoudre le problème de violation de la tension causé par le déséquilibre entre les charges et la génération de PV solaire, ainsi que les incertitudes associées à la nature intermittente de la génération de PV, dans les réseaux de distribution avec une forte pénétration de ressources PV. L'objectif est de développer une technique de contrôle robuste et évolutive qui peut gérer une forte pénétration de ressources d'énergie distribuée dans un réseau étendu en utilisant l'algorithme MDAJPM pour le contrôle de tension en optimisant le soutien de la puissance active et réactive dans un réseau à grande échelle.

La solution proposée est divisée en deux phases. Dans la première phase, le problème de contrôle de tension est formulé comme un problème d'optimisation à l'aide de l'algorithme MDAJPM pour réguler les tensions dans une limite acceptable avec une convergence rapide. L'approche prend en compte à la fois la puissance active et réactive des PV dans les systèmes de distribution d'énergie à forte pénétration de PV. Dans la deuxième phase, une stratégie de contrôle de tension coordonnée pour les onduleurs PV intelligents et les SSEB est développée pour allouer la capacité de puissance des SSEB et minimiser la perte de puissance active, ainsi que pour atténuer les violations de tension. Cette phase détermine la taille optimale des unités virtuelles de SSEB dans le réseau de distribution et minimise les pertes de puissance active grâce à la coordination des onduleurs intelligents PV et SSEB. La politique de contrôle garantit une régulation active efficace de la tension en absorbant ou en injectant la puissance active minimale et en chargeant ou déchargeant les SSEB pendant les périodes de génération PV et de demande de pointe.

Cette thèse vise à développer un nouveau schéma de contrôle actif qui aborde les problèmes de hausse et de baisse de tension tout en maintenant les profils de tension dans les limites permises et en diminuant les pertes. La méthode de dimensionnement de SSEB fournie par les onduleurs photovoltaïques-batteries aide à minimiser les pertes d'énergie PV. La formulation d'optimisation de chaque agent prend en compte les paramètres variables et les incertitudes associées à la génération d'énergie solaire et aux demandes de charge. L'algorithme MDAJPM contrôle les onduleurs PV intelligents localement et alloue les taux de charge/décharge des SSEB en fonction de la réduction minimale. Cette méthode intelligente démontre la capacité des onduleurs intelligents à gérer les incertitudes liées à la production d'énergie solaire photovoltaïque et à fournir un support de tension grâce à la puissance active ou réactive.

Enfin, la méthode proposée est évaluée à l'aide de MATLAB/Simulink et de MATPOWER sur des systèmes de distribution modifiés de 13, 33 et 141 bus de l'IEEE. Les résultats démontrent l'efficacité, la robustesse et la scalabilité du schéma distribué pour l'amélioration de la tension et l'utilisation optimale de l'énergie solaire photovoltaïque dans divers scénarios.

Mots-clés : Solaire photovoltaïque (PV), contrôle de tension, système multi-agents, systèmes de stockage d'énergie par batterie (SSEB)., méthode de direction alternée jacobienne proximale des multiplicateurs (MDAJPM)

ADMM-based Multi-Objective Control Scheme for Mitigating the Impact of High Penetration DER Integration in the Modern Distribution Systems

Sadaf RAHIMI FAR

ABSTRACT

The integration of renewable energy sources in modern distribution networks has introduced challenges for grid voltage regulation. In light of this, the present study proposes a multi-agent distributed voltage control strategy that utilizes the proximal Jacobian alternating direction method of multipliers (PJ-ADMM) algorithm for distribution power systems with a high penetration of photovoltaic (PV) resources coordinated with battery energy storage systems (BESS). The study aims to address the voltage violation issue caused by the mismatch between loads and solar PV generation, as well as uncertainties associated with the intermittent nature of PV generation, in distribution networks with a high penetration of PV resources. The objective is to develop a robust and scalable control technique that can handle the high penetration of Distributed Energy Resources (DERs) in an extensive network using the JP-ADMM algorithm for voltage control by optimizing the active and reactive power support in a large-scale network.

The proposed solution is divided into two phases. In the first phase, the voltage control problem is formulated as an optimization problem using the PJ-ADMM algorithm to regulate the voltages within an acceptable limit with fast convergence. The approach considers both the active and reactive power of PVs in high PV penetration distribution power systems. In the second phase, a coordinated voltage control strategy for smart PV inverters and BESS is developed to allocate the power capacity of the BESSs and minimize the active power loss, as well as mitigate voltage violations. This phase determines the optimal sizing of virtual BESS units in the distribution network and minimizes active power losses through the coordination of PVs and BESSs smart inverters. The control policy ensures efficient active voltage regulation by absorbing or injecting the minimum active power and charging or discharging the BESS during both PV generation and peak demand periods.

This thesis aims to develop a novel active control scheme that addresses voltage rise and drop issues while maintaining voltage profiles within permissible limits and decreasing losses. The BESS-sizing method provided by photovoltaic-battery inverters helps minimize PV energy loss. The optimization formulation of each agent takes into account variable parameters and considers uncertainties associated with solar energy generation and load demands. The PJ-ADMM algorithm controls smart PV inverters locally and allocates the charging/discharging rates of the BESS based on minimum curtailment. This intelligent method demonstrates the ability of smart inverters to handle PV uncertainties and provide voltage support through either active or reactive power.

Finally, the proposed method is evaluated using MATLAB/Simulink and MATPOWER on modified IEEE 13-bus, 33-bus, and 141-bus distribution systems. The results demonstrate the effectiveness, robustness, and scalability of the distributed scheme for voltage improvement and optimal utilization of PV power under various scenarios.

Keywords: Solar photovoltaic (PV), voltage control, multi-agent system, battery energy storage systems (BESS), proximal Jacobian alternating direction method of multipliers (PJ-ADMM).

TABLE OF CONTENTS

Page

INTRODUCTION 1

CHAPTER 1 LITERATURE REVIEW 15
1.1 Sustainable power system 15
1.2 Distributed renewable energy resources 19
1.3 Challenges associated with high penetrations of RESs to the distribution network....21
1.4 Different control approaches to solve overvoltage issue 22
1.5 Battery energy storage system for voltage regulation.....................................24
1.6 Microgrid control 26
1.7 Architectures of microgrid control..28
1.7.1 Centralized control 29
1.7.2 Decentralized control 30
1.7.3 Hierarchical voltage control.. 32
1.7.4 Distributed multi-agent control... 35
1.8 The control scheme for the distribution grid using smart inverter..................36
1.9 Voltage control using active and reactive power 38
1.10 Optimization-based control algorithm 40
1.11 ADMM-based control algorithm 41

CHAPTER 2 ADMM –BASED MULTI-OBJECTIVE CONTROL FOR MITIGATING THE IMPACT OF HIGH PENETRATION PV INTEGRATION IN DISTRIBUTION SYSTEMS 45
2.1 Introduction...45
2.2 Methodology 53
2.2.1 Problem formulation 53
2.2.2 Voltage sensitivity 56
2.2.3 ADMM method... 57
2.2.4 PJ-ADMM algorithm 59
2.3 Verification 63
2.3.1 Case study 63
2.3.2 Scenario I 65
2.3.3 Scenario II... 67
2.3.4 Scenario III.. 68
2.3.5 Scenario IV 69
2.4 CONCLUSION..73

CHAPTER 3 DISTRIBUTED COORDINATED VOLTAGE CONTROL OF PV-BESS FOR POWER LOSS REDUCTION...76
3.1 Introduction...76
3.2 Methodology 80
3.2.1 Proposed coordinated control strategy.. 80
3.2.2 PV uncertainty model 81

3.2.3 Optimization-based voltage control 82
3.2.4 BESS sizing 83
3.2.5 BESS operation constraints: 86
3.3 Validation........ 89
3.3.1 Case studies........ 89
3.3.2 IEEE 33-bus test system 89
3.3.3 IEEE 141-bus test system 94
3.4 Conclusion 100

CONCLUSIONS AND RECOMMENDATIONS 102

APPENDIX I 106

LIST OF BIBLIOGRAPHICAL REFERENCES........ 120

LIST OF TABLES

Page

Table 2.1 Results under scenario II....67

Table 2.2 The total amount of curtailment in the system....70

Table 2.3. Active and reactive power in the swing bus at midday 70

Table 2.4 Maximum voltage (p.u.) in buses 634 and 633 at midday....73

Table 3.1 The ratio of PV generation compares to the load. 90

Table 3.2 Power loss reduction with BESs....97

LIST OF FIGURES

Page

Figure 1.1 Traditional unidirectional grid power flow (Campbell, 2018)..................17

Figure 1.2 Bi-directional grid structure (Campbell, 2018)..18

Figure 1.3 General BESS applications..25

Figure 1.4 Different DERs in MG distributed control (Nazir et al., 2020)................27

Figure 1.5 Different architectures of Microgrid Control...31

Figure 1.6 Hierarchical control (Ishaq et al., 2022)..33

Figure 2.1 Simple passive distribution system...46

Figure 2.2 Simple active distribution system...47

Figure 2.3 Voltage profiles of distribution network. (a)Voltage rise; (b) Voltage drop..48

Figure 2.4 The basic structure of a distribution system with multiple PV agents.......54

Figure 2.5 Centralized voltage control with two-way communication system...........55

Figure 2.6 General Configuration of case study..63

Figure 2.7 Load and PV profiles...65

Figure 2.8 (a) 24h voltage profile of the system without control, (b) voltage profile with control under the scenario I, and (c) voltage profile with control under scenarios I and II..66

Figure 2.9 Voltage regulation under scenario III..68

Figure 2.10 Voltage regulation under scenario IV..69

Figure 2.11 Active and reactive power curtailment at bus-634 under scenarios III and IV...71

Figure 2.12 Voltage convergence at bus 634 at 12:00...72

Figure 3.1 General outline of the proposed coordinated control system.....................84

Figure 3.2 Overview of an interface between MATPOWER and YALMIP..............88

Figure 3.3 Configuration of case study on 33-bus system 90

Figure 3.4 Voltage profiles of 33-bus system with no voltage control 91

Figure 3.5 The 24h voltage profile of 33-bus network with PV-BES voltage control 92

Figure 3.6 BESS participation in 33-bus system..93

Figure 3.7 Voltage profiles of 141-bus system with no voltage control 94

Figure 3.8 The 24h voltage profile of 141-bus network with PV-BES voltage control 95

Figure 3.9 Charging discharging rate (MW) for each BESS in 141-bus system 96

Figure 3.10 Voltage convergence at node 29 at 13:00 98

Figure 3.11 Voltage profile with and without control compared with BESS at node 28..99

LIST OF ABBREVIATIONS

DER	Distributed Energy Resources
RES	Renewable Energy Sources
PV	Photovoltaic
DG	Distributed Generation
PJ-ADMM	Proximal Jacobian ADMM
BESS	Battery Energy Storage Systems
MAS	Multi-Agent Systems
IEA	International Energy Agency
NZE	Net Zero Emissions
OLTC	On-Load Tap Changers
PCC	Point of Common Coupling
ADMM	Alternating Direction Method of Multipliers
MG	Microgrid
DD	Dual Decomposition
MPC	Model Predictive Control
DALM	Distributed Augmented Lagrangian Method

LIST OF SYMBOLS AND UNITS OF MEASUREMENT

V	Voltage (V)
P	Active power (Kw)
Q	Reactive power (kVAr)
V^{min}	Minimum voltage
V^{max}	Maximum voltage
n	Number of PV inverters
N	Set of PV inverters
V^{t}	Voltage magnitude at the PCC
L	Lagrangian Function
t	Time step
k	Iteration
ΔP	Change in active power
ΔQ	Change in reactive power
F^{P}	Constant penalty factor of P
F^{Q}	Constant penalty factor of Q
C_u	Active power curtailment factor
P^{pv}	PV power output
S_n	Apparent power
V^{M}	Measured voltage
ρ	Augmented penalty factor
λ	Lagrangian multiplier
U_n	Acceleration factor

τ	Active power curtailment factor
η_{ch}	Charging efficiency of the battery
η_{dch}	Discharging efficiency of the battery

INTRODUCTION

0.1 Context and Motivation

In recent decades, power systems have experienced significant expansion in distributed energy resources (DERs). DERs are considered power sources or controllable loads connected to the distribution power network, such as Renewable Energy Sources (RES) and storage systems (IEA, 2020a). The adoption of RESs technologies in the grid improves the sustainability and economics of distribution systems. The growing integration of RESs, such as wind and solar energy sources, is key to mitigating carbon dioxide emissions and decarbonizing the energy sector. Driven by ever-increasing efforts, most developing countries have invested in clean energy in response to increased environmental concerns.

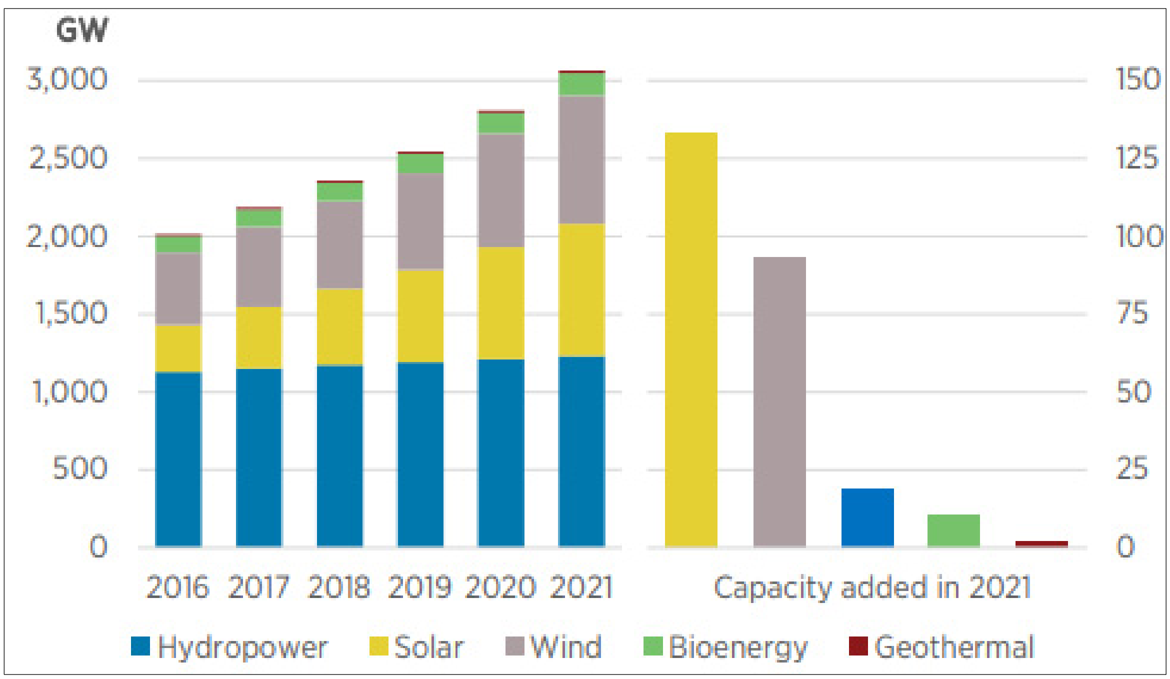

Figure 0.1 Renewable power capacity growth (IRENA, 2022)

The utilization of renewable energy sources plays a crucial role in the progression towards clean energy and the mitigation of the increase in average global temperatures to below 1.5°C. At the end of 2021, worldwide renewable energy generation capacity has experienced tremendous growth (Figure 0.1) reaching 3 064 GW (IRENA, 2022). Although promising advancements have been made, with 2022 estimated to set a new record for renewable capacity additions, reaching approximately 340 GW, further expansion is necessary to meet the objectives of the Net Zero Emissions by 2050 Scenario (Bouckaert et al., 2021). The NZE is a normative International Energy Agency (IEA) scenario that provides a pathway for the global energy sector to achieve zero greenhouse gas emissions in the atmosphere. This scenario calls for an increase in the renewable share of generation from nearly 29% in 2021 to over 60% by 2030 and a yearly average increase of 12% during the period from 2022 to 2030, which is double the average increase observed from 2019 to 2021 (IEA, 2020a).

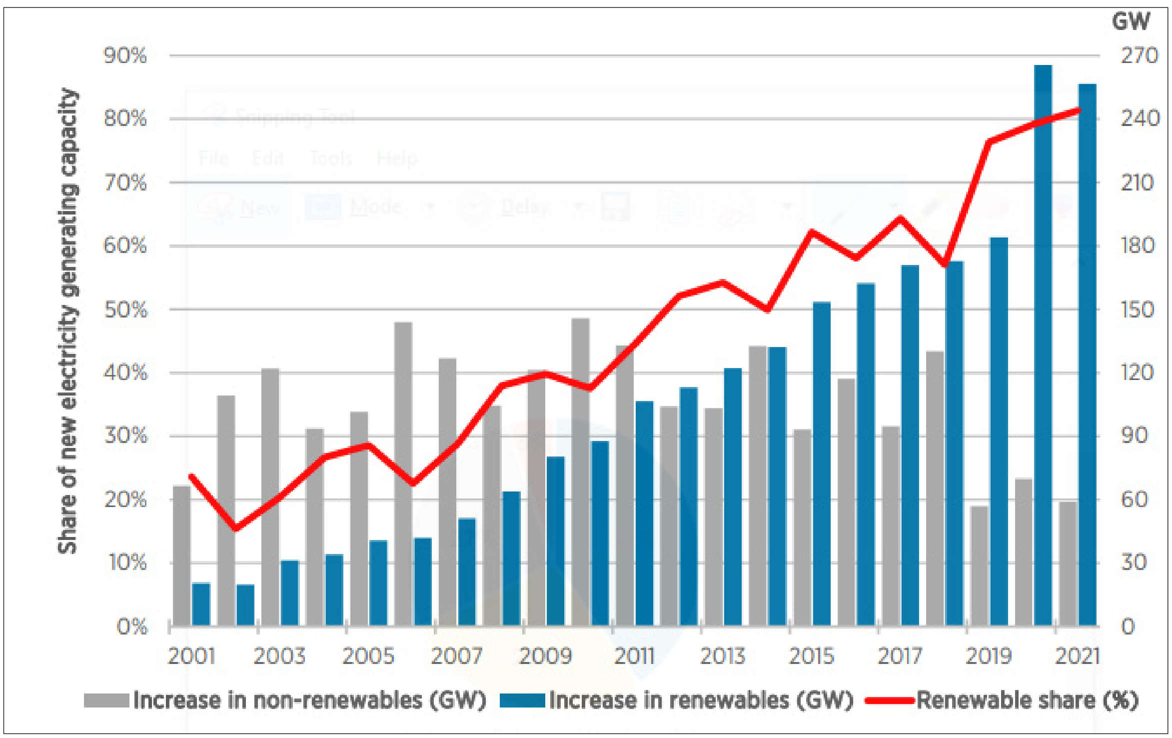

Figure 0.2 Renewable's share of power capacity growth annually (IRENA, 2022)

In the year 2021, the increase in renewable energy generation capacity saw a slight decline compared to the previous year (Figure 0.2), though it still remained much higher than the historical average. China was responsible for the majority of this growth, followed by the United States, while other nations continued to expand their renewable energy capacity at a steady rate. The percentage of renewable energy the overall increase in capacity was 81% in 2021, as opposed to 79% in 2020.

This positive trend in the use of renewable energy is a demonstration of the swift and increasing implementation of renewable sources and the decreasing expansion of non-renewable capacity, particularly due to widespread decommissioning in certain regions over time. In 2021, while non-renewable capacity continued to grow in Asia, the Middle East, and Africa, growth in the Middle East and Africa experienced a significant reduction and decommissioning continued in Europe and Eurasia. To achieve a successful transition to clean energy, the use of renewables must increase at a faster rate than energy demand, thus decreasing the dependence on non-renewable sources. Despite the considerable rise in the utilization of renewables for electricity generation, many nations have yet to reach this goal.

Renewable electricity generation experienced remarkable growth in 2021, with a record increase of 522 TWh, representing a near 7% rise. The bulk of this expansion was attributed to wind and solar PV technologies, which combined accounted for approximately 90% of the growth. Despite this notable growth, the share of renewables in overall electricity generation remained modest, reaching 28.7% in 2021 with a mere 0.4 percentage point increase. The gradual growth rate can be attributed to a multitude of causes, one of which is the resurgence of economic activity following the Covid-19 slowdown and decreased hydropower generation due to droughts in various regions, resulting in global electricity demand reaching its highest level in history.

Despite the difficulties associated with the 2021 pandemic, photovoltaic technology has experienced visible annual capacity growth (IEA, 2020a). Solar Photovoltaic power is one of the most promising renewable energy technologies and plays a substantial role on a global level of energy in the world. The global market for photovoltaic systems has been increased significantly in recent decade. According to IRENA (2022), solar power accounted for approximately one-third of the total renewable electricity generation growth, with the highest annual increase in generating capacity globally, with an increase of 133 GW (+19%), followed by wind energy with 93 GW (+13%).

The global solar and wind energy capacities reached approximately the same level in 2021, with capacities of 849 and 825 GW, respectively (IRENA, 2022). However, solar PV and wind costs are expected to remain higher in 2023 than in the pre-pandemic period because of increased commodities and transport prices. The rapid growth of solar PV integration in power systems poses complex challenges in controlling power distribution networks and maintaining the power supply-demand balance, which highly stresses modern networks in operation (Sun et al., 2019). Moreover, solar PV integration introduces significant uncertainties and intermittency, which have induced various technical challenges such as the voltage rise problem and voltage flicker phenomena that can negatively affect stability, security, and reliability in the distribution grid. Thus, a major concern is the voltage deviation when the voltage profile of the system exceeds an acceptable range.

The two-directional power flow in modern grids is continuously monitored at each connection point between utility customers to track the risk of reverse power flows. The major issue in this system is reverse power flow, which can create overvoltage issues during high PV generation periods. Moreover, the intermittency of PV resources may cause unexpected voltage fluctuations in distribution networks (Kabirifar, Pourghaderi, Rajaei, Moeini-Aghtaie & Safdarian, 2020). High solar PV generation and low load demand cause voltage rise issues, which mostly occur at midday in summer (Wang et al., 2020). Moreover, a rapid drop in PV generation during high electricity demand can potentially cause an undervoltage problem in modern distribution systems. Both overvoltage and undervoltage violations are considered as major challenges in solar PV penetration

The modern power grid is being upgraded with new technologies to manage the system on both the electricity generation and demand side (Mohan, Hasan, Gebremariam & Varma, 2018). Grid voltage regulation plays a crucial part in ensuring the stability of contemporary power grids during instances of power generation-load demand imbalance. The traditional solution to overcome voltage problems in distribution networks includes 1) grid reinforcement which includes upgrading the distribution system by increasing its capacity, which is costly, 2) utilities traditionally regulate voltages utilizing voltage regulation devices such as on-load tap changers (OLTC) and capacitor banks. However, in highly penetrated networks, these control devices cannot provide a fast response to fluctuations in renewable power, and 3) curtailment of solar PV generation to alleviate the voltage rise and limit the excess power being injected into the distribution system during high electricity generation. However, this approach results in energy loss which is not preferable (Wang et al., 2015).

In this context, an alternative solution is to implement advanced voltage control features through PV inverters. With the recent update of the IEEE 1547 standard (Photovoltaics & Storage, 2018), smart PV inverters can contribute to voltage regulation at their point of common coupling (PCC) with the distribution system by providing both active and reactive power control functions. This way, smart inverters can inject/absorb reactive power or curtail active PV power to support the grid voltage under loading conditions (Alyami, Wang, Wang, Zhao & Zhao, 2014). However, curtailing the active power affects the PV owner's revenue by limiting the solar PV power capacity. In this regard, a solution to mitigate voltage deviation and minimize energy loss is to couple PV inverters with a battery energy storage system (BESS) (Ranaweera, Midtgård & Korpås, 2017).

Battery energy storage system technology has been experiencing rapid development as an effective tool for managing grids and improving the functionality of smart grids. It is a crucial technology in the shift towards a sustainable energy system. It provides a range of services crucial for the energy transition, and grid support. Battery systems can also be employed to store energy in electric vehicles, and promote the utilization of solar power on rooftops. These systems are playing a crucial role in integrating renewable energy sources, such as solar and wind, into the world's power systems. The most promising market for in the BES coming years is likely to be the combination of BES systems with small-scale solar PV installations.

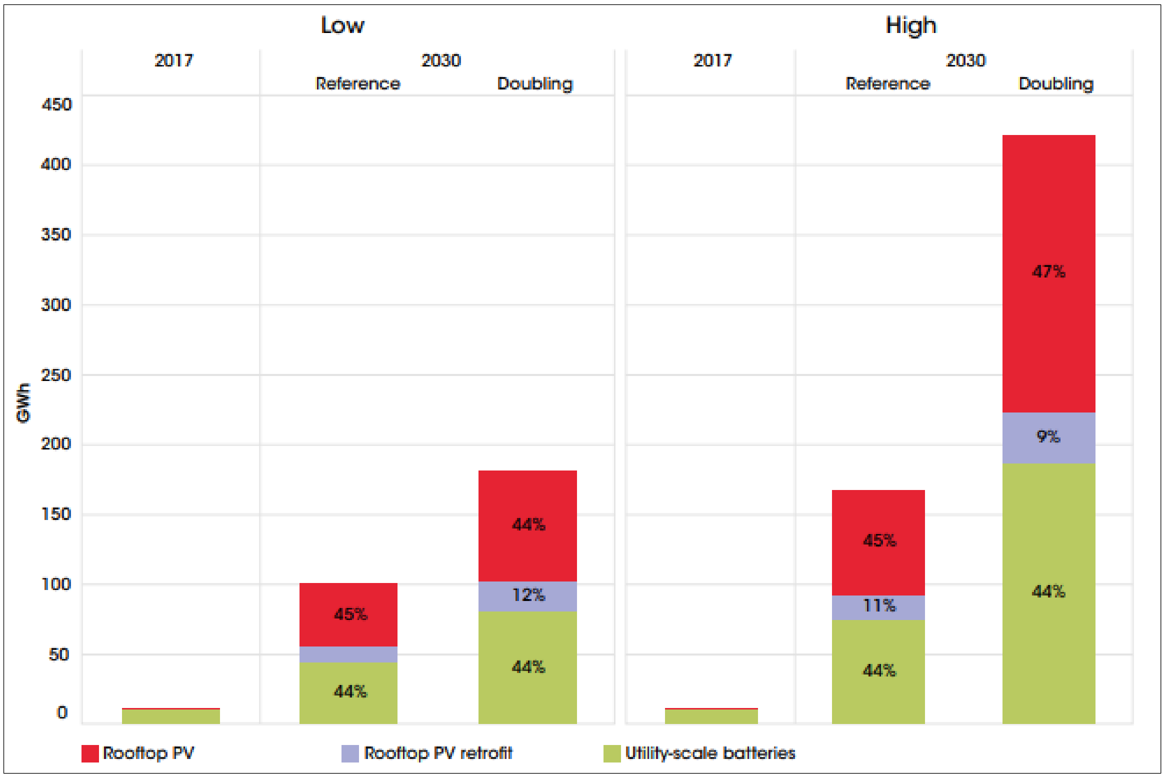

Figure 0.3 Battery storage growth in stationary applications by sector (IRENA, 2017)

The economics of using BES in these applications is expected to greatly improve since 2017, particularly in regions with high residential and commercial electricity rates, low grid feed-in remuneration, and competitive solar PV costs such as Europe. Australia, with its high electricity rates and favorable solar conditions, is also poised to become a significant market for BES. Japan may also present a new opportunity for BES, as declining support for rooftop solar PV combined with high electricity rates may make the economics of storage more attractive. The BES market in utility-scale projects is anticipated to experience robust growth, with estimates ranging from 45 GWh to 187 GWh by 2030 (IRENA, 2017). As nations put into effect market reforms to encourage increased utilization of renewable energy, new opportunities for supplementary services arise. such as frequency reserves and firm capacity will emerge, offering new opportunities for BES deployment. Additionally, BES technology's ability to provide renewable capacity firming and time shift services is also expected to expand.

BESS can control voltage levels by adding or subtracting power as needed to balance the difference between power generation and demand. When combined with photovoltaic inverters, BESS can regulate the power output (Le Dinh & Hayashi, 2013). However, the control of an intelligently coordinated PV-ESSS distribution system is challenging. Different techniques have been studied in the literature for controlling the voltage in the distribution network, which is categorized based on their architectures: centralized, decentralized, and distributed multi-agent systems (MAS) control.

A centralized control scheme uses a central decision-maker to locally organize all unit information in the network. A centralized controller has a simple scheme and requires point-to-point interaction as it controls power from a single point. However, it would not be a proper control architecture to perform operations in complex large-scale networks. Due to a lack of scalability, limited communication, and flexibility, a centralized controller can be always at risk of a single point of failure (Mokhtari, Nourbakhsh & Ghosh, 2013). The decentralized control of smart distribution systems can be achieved through coordination between individual units, and without the presence of a central controller (Ishaq et al., 2022). It has fewer requirements for interacting with other units; therefore, the decision process is local. Due to the lack of communication structure, local control has the advantage of being easy to implement. In this technique, each unit processes only local data without interacting with other units. Therefore, it does not offer comprehensive solutions for the entire system. Thus, the decentralized control method usually has low efficiency which affects power quality.

A promising approach to overcome above challenges is the distributed multi-agent control technique. Considering the complexity of distributed energy resources, traditional distribution systems are moving towards flexible multiagent structures. Recently, distributed control structures have attracted increasing attention in power system. In distributed management, each decision maker is called an agent, and each agent is responsible for managing its local resources and participating in data sharing in parallel with other agents. Moreover, this control method has a good potential for use in the high penetration of renewable systems with several agents, as it is robust and scalable. This method is suitable for controlling large-scale systems. Under a multi-agent control approach, each agent uses its local information and neighbour-to-neighbour communication network to achieve overall regulation in the system (Lewis, Zhang, Hengster-Movric & Das, 2014). Using distributed voltage control systems helps maintain sensitive constraints, and achieve global objectives. Consequently, it can improve the reliability, scalability and flexibility of the control performance in large-scale networks with complex computations.

Distributed optimization techniques have been used in several studies to implement distributed voltage control systems. Distributed control algorithms are mostly based on the Alternating Direction Method of Multipliers (ADMM) (Aziz, Peng, Wang & Jiang, 2019), which is used as the theoretical framework for optimizing distributed voltage control systems. Distributed intelligence control in this framework enables agents to interact with each other (Wang et al., 2018). It can also be used to optimize the RES inverter outputs in the MAS concept to maintain the voltage within an acceptable range by utilizing a reactive power support and minimum active power curtailment. The ADMM algorithm is an optimization technique for dealing with non-convex optimization problems in a fully distributed manner (Wang, Yan, Jin & Li, 2019).

Despite the advantages of iterative algorithms such as ADMM, the main challenges are its implementation, due to its complexity and low convergence rate. Moreover, active power curtailment no matter how little causes a loss of PV energy capacity, which is against the decarbonizing goals. In this context, the application of battery energy storage systems has a significant function to perform. A review of previous studies indicates that most of the literature focuses on optimizing functions related to the technical parameters of the network and BESS, optimal sizing, and the location of BESS in the system. To solve the above-mentioned problems and fill the gap in the literature, this thesis proposes a novel solution by coupling smart PV inverter features and BESS to ensure voltage regulation within constraints with minimum power loss. In light of the above considerations, the optimal utilization of PV power was ensured by controlling the smart PV inverters locally through the proximal Jacobian ADMM (PJ-ADMM) (Deng, Lai, Peng & Yin, 2019) algorithm in cooperation with the BESS. The application of additional penalty factors resulted in a faster voltage convergence. In this context, correctly setting the initial values of the parameters is crucial. The idea of storage sizing comes from a virtual curtailment strategy through the PJ-ADMM algorithm cycle by modifying the storage participation in voltage regulation, which gives rise to the efficient utilization of the BESS capability during power imbalance periods.

The smart coordinated control strategy can assist in voltage regulation by absorbing or injecting the minimal active and reactive power and managing the charging and discharging of BESS during periods of high demand and photovoltaic generation. This is achieved by utilizing energy storage systems to store surplus energy produced by renewable sources during low demand times, which can then be utilized during high demand periods. The aim is to minimize power loss and enhance voltage while considering constraints, including the minimum storage capacity as a technical requirement for voltage control. The proposed method provides a practical idea for overcoming the challenges arising from the high penetration of solar PV power such as the possibility of regulating power and voltage in the grid with minimum changes in its active power generated.

To the best of our knowledge, the application of the PJ-ADMM algorithm for voltage control in high penetration PV systems coupled with BESS in a fully distributed structure has not yet been investigated in previous studies. The proposed method operates in two phases under different scenarios. In the first phase, the voltage control problem is formulated as a multi-objective optimization method. In the second phase, the BESSs are integrated with smart PV inverters to store excess solar power and control voltage. The control policies considered determine the active and reactive powers of the PV inverters and the charge/discharge power of the batteries.

0.2 Objectives and scope

The proposed method aims to coordinate the active and reactive power of solar PV systems through smart inverters in the distribution network, utilizing BESS to maintain voltage within acceptable limits and minimize losses. The control process takes into account uncertainties from varying power generation and demand, and utilizes a centralized optimization problem that is divided into sub-problems solved by the system's agents in a distributed manner. The coordination of PV inverters and virtual BESS through a PJ-ADMM approach minimizes active power reduction and offers voltage support during overvoltage events through distributed reactive power contributions The specific objectives of this study are summarized as follows:

1. Voltage violation assessment in distribution systems with high DER penetration concentrates on overvoltage and undervoltage problems.
2. Development of an optimization-based distributed voltage control algorithm for smart PV inverters with fast convergence to mitigate the impact of high penetration DER integration in distribution systems (Phase I).

The sub-objectives of phase #1 were:

- Develop and program an interface between MATLAB-Simulink and YALMIP to exchange data.
- Ddesign and implement a modified 13-bus IEEE network using MATLAB-Simulink.
- Develop and implement a parallel voltage control technique based on the PJ-ADMM algorithm.
- The possibility of improving the voltage profiles with active power, reactive power, or both using the PJ-ADMM algorithm to minimize active power curtailment.
- Reactive power modulation for voltage improvement and satisfying load demand during undervoltage periods.
- Tuning the sensitive parameters of the JP-ADMM to find acceptable results through the trial-and-error method.
- Verify the distributed control system performance using the IEEE 13-bus test feeder.
-

3. An intelligent coordination method is designed to minimize energy loss by developing an optimization strategy that schedules battery operation to mitigate the overvoltage problem.
4. Development of a mathematical formulation based on the PJ-ADMM approach coordinated with BESS to satisfy the maximum participation of PV power in the

distributed operation of multi-objective control systems considering network uncertainty (phase II).

The sub-objectives of phase #2 were:

- Develop and implement an interface for a distributed optimization algorithm between MATPOWER and YALMIP.
- Development of a coordinated distributed voltage control algorithm for PV inverters and virtual storage to minimize power loss and regulate grid voltages.
- Validation of the performance of the control scheme in the high penetration level of PVs using the IEEE 33-bus and 141-bus test feeders.
- Evaluation of performance of distributed BESS response with respect to maximum PV hosting capacity.

0.3 Contributions

The main contribution of this thesis is to propose a new control technique capable of coordinating optimally the active and reactive power of the solar PV systems through smart inverters in the distribution network to maintain the voltage within the limits and reduce losses using BESS. The control method is conducted under uncertainties caused by unbalanced and variable power generation and load demands. To do that, the centralized optimization issue is separated into smaller sub-problems, which are then iteratively addressed by the individual components of the system in a decentralized manner. The coordinated control of the PV inverter and virtual BESS utilizing the PJ-ADMM method is Implemented. The main contributions of this study are:

- The development of an iterative multi-agent voltage control algorithm with a high convergence rate.
- The formulation of an optimal PJ-ADMM-based modulation strategy for active and reactive powers to enhance voltage and meet load demands during day and night operations through the deployment of smart inverters.

- The establishment of an analytical approach for coordinating PJ-ADMM with BESS for smart PV inverters, enabling maximum participation of PV power in multi-agent systems under network uncertainty.
- The identification of a method for optimal BESS sizing to maximize the utilization rate of PVs with PJ-ADMM for power loss reduction.
  The establishment of a framework for demonstrating the scalability of the proposed algorithm in large-scale and complex distribution power systems.

0.4 Thesis outline

The present thesis is comprised of four distinct chapters. In Chapter 1, a comprehensive literature review and relevant theoretical background are presented to provide a solid understanding of the concepts and techniques utilized in the following chapters. This section serves as a foundation for the fundamental arguments that are essential for comprehending and applying the multi-objective control method.

Chapter 2 proposes an optimization-based distributed voltage control scheme and details its implementation. The high convergence speed of the control scheme is achieved by incorporating the PJ-ADMM into smart PV inverters. Several scenarios are simulated to enhance the performance of the proposed algorithm under varying loads and PV uncertainty. The effectiveness of the proposed algorithm is verified through testing on an IEEE 13-node test feeder, which showcases how optimal integration of PVs and smart inverters can help maintain voltage within constraints, ultimately reducing active and reactive power losses in the distribution network.

In Chapter 3, the proposed control scheme is further optimized and extended to incorporate the integration of smart PV inverters and virtual storage systems in regulating voltage profiles with minimum power loss. In this section, a modified 33-bus and 141-bus network serves as a case study to showcase the robustness and scalability of the suggested voltage control system. The MATPOWER software is utilized to solve power flow, while the YALMIP is utilized for optimization purposes. Two scenarios are considered in the large-scale distribution system, incorporating uncertainties such as PV power generation and user consumption. The results show that the optimized functions of the smart PV inverter and battery energy storage systems can regulate voltage profiles effectively, without incurring PV power loss, thus verifying the optimal improvement and robustness of the control scheme.

The main part of this dissertation includes Chapters 2 and 3, which have been published in a journal paper. The paper titled "ADMM-Based Multi-Objective Control Scheme for Mitigating the Impact of High Penetration DER Integration in the Modern Distribution Systems" by S. R. Far, A. Moeini, A. Chandra and I. Kamwa was published in IEEE Access, vol. 11, pp. 38589-38603, 2023.

The final chapter summarizes the entire thesis and proposes recommendations for future work and possible avenues for further research on this topic

CHAPTER 1

LITERATURE REVIEW

This chapter presents a comprehensive review of the existing literature on the challenges of integrating renewable energy sources (RES) and the optimal solutions using distributed control methods. It begins with a general overview of the distribution network and the technical difficulties encountered in highly penetrated networks, including a discussion of voltage issues. The various control methods used to address overvoltage problems are then reviewed. The integration of BESS and PV in power networks is also discussed. The chapter ends with a description of a multi-agent, distributed voltage control technique for distribution networks with high photovoltaic penetration.

1.1 Sustainable power system

The electric power system is a crucial infrastructure that has been developed over the past century to meet the energy demands of consumers and satisfy their needs (Grigsby, 2007). Electricity is delivered to consumers through a complex system, comprising three main sections: generation, transmission, and distribution (Weedy, Cory, Jenkins, Ekanayake & Strbac, 2012). In the generation component, electric power is produced in generator units, which are often located far from load centers. These units may be powered by various energy sources, including fossil fuels, nuclear energy, and renewable energy sources such as wind and solar. The generated power is then transmitted through power lines that connect power suppliers to end users, requiring long-distance transmission. The transmission component of the power system involves the transmission of power from the generation sources to the distribution system, which is responsible for delivering power to final consumers. The distribution system refers to the final section of the power system, consisting of a network of distribution lines and substations that deliver transmitted electric energy to loads such as homes and businesses (Sallam & Malik 2018).

In the past, traditional power systems were fueled by fossil fuels such as coal, oil, and natural gas (Wang, Syed, Guillo-Sansano & Burt 2018). Although these energy sources are readily accessible and comparatively economical, their utilization results in significant adverse environmental consequences, including greenhouse gas emissions, air pollution, and degradation of habitats. As the negative consequences of fossil fuel-based power systems have become more apparent, there has been an increasing shift towards the adoption of renewable energy sources as a means of reducing these impacts and transitioning to a more sustainable energy system.

Renewable energy sources, such as wind and solar power, offer an alternative to fossil fuels because they are widely available, have low or zero emissions, and have a much lower environmental impact compared to fossil fuel-based power systems (Shuai, Fang, Ning & Shen, 2018). The demand for renewable energy power plants in electric power grids is increasing due to their availability, positive environmental impact, and decreasing costs. In recent years, the cost of renewable energy technologies, such as PV systems, has significantly decreased, making them more competitive with fossil fuels. Incentives and subsidies for renewable energy have also contributed to the increased adoption of these technologies worldwide (Xu, Xue & Chang, 2021).

The increasing adoption of renewable energy sources in the power system has been driven by a variety of factors, including concerns about climate change, the need to reduce greenhouse gas emissions, and the falling cost of renewable energy technologies. According to the International Energy Agency (IEA), the share of renewable energy in global power generation is expected to continue to grow in the coming decades, with solar and wind power expected to be the primary sources of new capacity. The transition to renewable energy has gained significant momentum in recent years due to a combination of environmental, economic, and policy considerations. In 2019, the energy sector was responsible for approximately 75% of global CO2 emissions, making it a critical focus for decarbonization efforts (IEA 2019). As a result, there is increasing consensus that a shift to cleaner, renewable energy sources is necessary to address these issues.

In recent years, there has been a rapid expansion of renewable energy resources in power systems as a way to reduce negative impacts on the environment and transition to a more sustainable energy system. Renewable energy sources, such as wind and solar power, have seen significant growth in recent years due to their availability, positive environmental impact, and decreasing costs. Among these renewable energy resources, photovoltaic systems have experienced particularly the highest annual growth rate for installed capacity among other renewable energy resources due to their low installation and maintenance costs and high scalability (Cozzi et al., 2020). The increase in renewable energy resources has necessitated the development of new power generation technologies that can enhance system performance in distribution systems.

Over the past two decades, there have been significant advances in solar energy technologies that have made it possible to more effectively integrate these resources into power systems. However, the electric power system has typically been designed with a unidirectional power flow, transmitting power from the high-voltage side of electric utilities to the low-voltage side of users. This means that electricity flows in a single direction, from the generation sources to the end users, as illustrated in Figure 1.1 (Campbell, 2018).

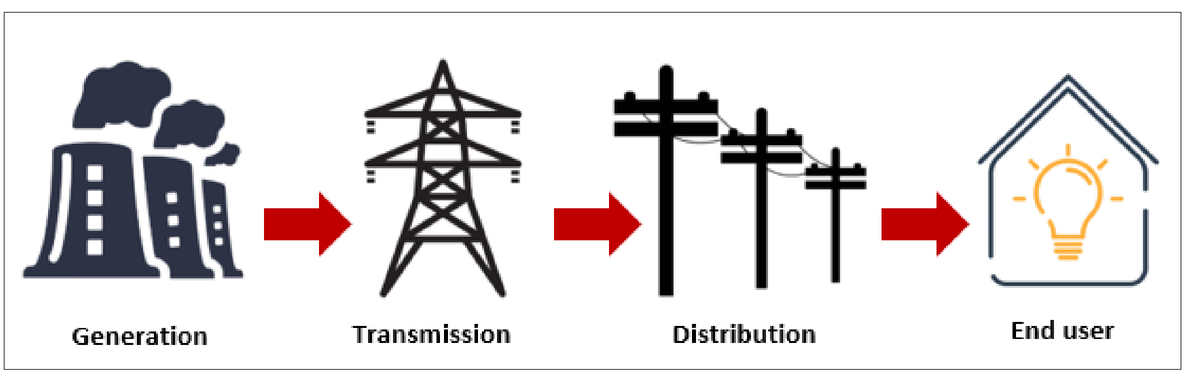

Figure 1.1 Traditional unidirectional grid power flow (Campbell, 2018)

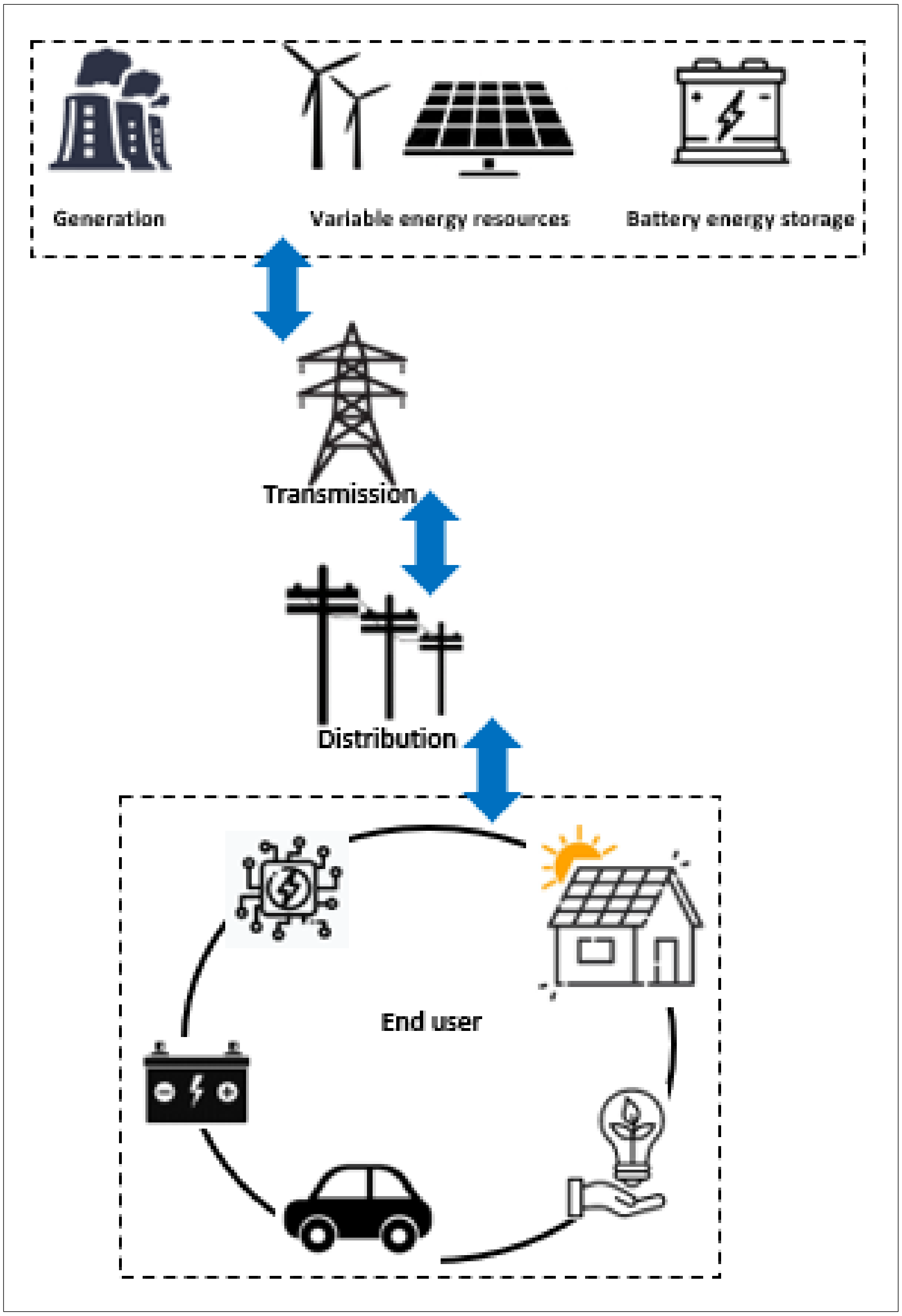

Figure 1.2 Bi-directional grid structure (Campbell, 2018)

The integration of RESs into the power system has posed several challenges, including the need to address the intermittent nature of many RESs and the requirement for advanced technologies such as energy storage systems and smart grids to enhance system performance.

As the use of RESs in power systems has increased, there has been a need to develop technologies that can effectively manage the complex power flows of modern power systems (Campbell, 2018). One solution that has been implemented in recent years is the use of smart grid technologies, which enable two-directional power flow and improved system management. These technologies allow the power system to more effectively integrate RESs such as wind and solar power, which can be intermittent and difficult to forecast.

Smart grid technologies have the potential to enhance grid operation and provide increased flexibility and efficiency to the system. Energy storage systems, for example, can store excess renewable energy for use when needed, thereby mitigating the fluctuations in power supply and demand often associated with renewable energy sources. Other smart grid technologies, such as state-of-the-art metering infrastructure and decentralized generation, can enhance system efficiency and augment the power system's robustness. As depicted in Figure 1.2, the use of smart grid technologies enables two-directional power flow in modern grids. By leveraging these technologies, power systems can become more sustainable, reliable, and resilient in the long term.

1.2 Distributed renewable energy resources

Distributed renewable energy sources are a key component of modern power grids, comprising a range of energy devices such as residential solar panels, electric vehicles, and battery energy storage systems. These distributed energy resources are connected to the grid at various levels and exhibit diverse demand and supply characteristics. DERs, particularly RESs and energy storage systems, are viewed as crucial resources that can be integrated into the electric grid to support government policies and enhance the grid's efficiency, sustainability, reliability, and privacy. The term "smart grid" refers to control and communication technologies incorporated into traditional power grids to improve their performance. The smart grid is able to balance the system load by controlling electricity demand through power flows and exchanging data and information between different DER units. To enable this, a robust communication infrastructure is required for efficient operation and improved grid reliability.

In addition to their role in supporting government strategies and improving the overall performance of the power grid, DERs have the potential to provide several other benefits. For example, DERs can increase the reliability and resiliency of the power grid by providing multiple sources of energy generation and storage distributed throughout the grid, reducing the risk of widespread outages. They can also help to reduce greenhouse gas emissions, as many DERs generate electricity using clean, renewable energy sources. By increasing the use of these resources, the power grid can become more environmentally friendly and sustainable.

DERs can also be configured to mitigate voltage fluctuations and harmonics in regions with substantial nonlinear loads and improve energy efficiency through decentralized optimization methods (Xu, Xue & Chang, 2021). Energy storage systems can provide emergency power to the network and assist in managing load demand or renewable power generation. However, it is worth noting that the reverse power flow and intermittent nature of DERs can result in technical challenges such as power losses and over-voltage concerns (Tonkoski, Turcotte & El-Fouly, 2012). Furthermore, the integration of DERs into the power grid can potentially lower electricity costs for consumers. By generating electricity locally rather than relying on large, centralized power plants, the cost of transmitting electricity over long distances is reduced, resulting in lower electricity prices for consumers. Overall, the use of distributed energy resources is expected to play a significant role in the future of the power grid as we transition towards a more sustainable and reliable energy system.

There are numerous advantages to incorporating distributed energy resources into the modern power grid. One of the main benefits is the ability of DERs to increase the grid's reliability and resiliency. By having multiple sources of energy generation and storage distributed throughout the grid, the risk of widespread outages is reduced. In addition, DERs can help to alleviate the burden on the grid during times of high demand, leading to improved overall system efficiency. Another advantage of DERs is their potential to decrease greenhouse gas emissions. Many DERs, such as solar panels and wind turbines, generate electricity using clean, renewable energy sources. By increasing the use of these resources, the power grid can become more environmentally friendly and sustainable.

1.3 Challenges associated with high penetrations of RESs to the distribution network

Distribution networks were not originally designed to accommodate the large-scale integration of intermittent RESs, such as solar PV systems (Bai,Yan, Saha & Eghbal 2020). As a result, the increasing penetration of these alternative power resources is becoming a growing concern for maintaining a balance between supply and demand on distribution networks (Sun et al., 2019). The intermittent nature of PV systems can cause imbalances between supply and demand, especially in large-scale systems, which can lead to instability and negative effects on the voltage of distribution networks, such as voltage fluctuations and flicker (Impram, Nese & Oral, 2020). These issues have put stress on the power system and have caused some power quality concerns, such as reliability and stability challenges. Some of these challenges have been addressed in the literature through the use of control and mitigation techniques for addressing the negative impacts of DERs on voltage deviation (Kabirifar, Pourghaderi, Rajaei, Moeini-Aghtaie & Safdarian, 2020). In some cases, these issues can even lead to complete blackouts on the network.

Renewable energy sources such as solar and wind power have become increasingly prevalent in the distribution system, but integrating them into the grid presents significant challenges. One major challenge is the voltage level of the network. In passive networks, if the production of a RES feeder exceeds the consumption, the excess power will flow back into the network, a phenomenon known as opposite power flow. This can lead to voltage instabilities in the power supply, which can negatively impact connected loads and devices. To ensure the smooth operation of all elements in the power system, it is necessary to maintain voltage levels within certain limits. However, the power fluctuations often associated with RESs can result in either over-voltage or under-voltage (Wang,Syed, Guillo-Sansano, Xu, & Burt, 2019). An over-voltage occurs when the voltage exceeds the upper limits, potentially damaging electrical components and devices. On the other hand, a voltage drop in the distribution network can lead to system overload. Both of these situations can result in inefficient equipment operation for users.

One potential solution to these challenges is the use of advanced control systems and smart grid technologies, which can help to stabilize voltage levels and mitigate the impact of power fluctuations from RESs. For example, voltage regulators and reactive power compensators can be used to regulate the voltage at different points in the distribution network. In addition, distributed energy resources such as energy storage systems can be deployed to store excess energy and help balance supply and demand. Another approach is to use dynamic pricing schemes, which can incentivize consumers to shift their energy consumption to periods of low demand, reducing the strain on the grid and helping to stabilize voltage levels. Overall, addressing the challenges associated with high penetrations of RESs in the distribution network will require a combination of technological solutions and changes to current operating practices. By finding ways to effectively integrate RESs into the grid, it will be possible to harness the full potential of these clean and renewable energy sources.

1.4 Different control approaches to solve overvoltage issue

Maintaining the voltage profile within an appropriate range is a crucial aspect of power system analysis. A number of approaches have been proposed to address the voltage rise issues that can arise with high levels of PV penetration. One solution is to enhance the system infrastructure by installing additional cables or upgrading transformers (Aziz & Ketjoy, 2017). However, this option is costly and may increase maintenance costs. On-load tap changers, a type of autotransformer, can also be used to mitigate overvoltage by adjusting voltage within predetermined limits (Hu, Marinelli, Coppo, Zecchino & Bindner, 2016). However, the capricious nature of solar power generation and consumption in networks with substantial photovoltaic penetration may result in frequent tap changer switching, which can negatively impact autotransformer operation and increase costs.

Various control techniques have been proposed to address voltage rise in modern power systems, including the use of storage systems in distribution systems and load regulation through demand-side management. In stable networks, DERs can play a role in active control of the modern distribution system. When a large number of DERs are integrated into a network, computation becomes more complex. One approach to addressing this complexity is to divide the system into smaller sub-systems, each with a limited number of DERs to be controlled optimally. To achieve this, robust control systems must be in place to actively monitor the distribution grid.

PV inverters offer various technical capabilities, including reactive and active power control. Controlling reactive power can be a highly effective approach to manage overvoltage in networks that have a high penetration of renewable energy sources such as photovoltaic inverters (Varma, 2021). Smart photovoltaic inverters can assist in regulating voltage levels by absorbing reactive power in order to prevent overvoltage, particularly when a voltage limit violation is detected Active power curtailment is another approach to mitigating overvoltage in the distribution network. This method involves limiting active power from PV when PV power generation exceeds load consumption. Voltage constraints, which are set to ensure safe and secure operation of the network, are a statutory standard for voltages. The economic benefits of PV owners are depended on maximizing the output from the facility. So, this method is against the economic aims of installing PV for owners which is the disadvantage of the power curtailment approach (Ghosh, Rahman& Pipattanasomporn, 2014).

One approach to address overvoltage in the distribution network is the use of reactive power control through PV inverters. This method involves the absorption of reactive power by smart PV inverters to limit overvoltage when a voltage limit violation is detected. This can be an effective solution in networks with high penetration of renewable energy sources, such as solar PV systems. However, this approach may not always be feasible, as it may be at odds with the economic interests of PV owners, who typically aim to maximize the output of their facilities. Another method for mitigating overvoltage in the distribution network is active power curtailment. This involves limiting the active power from PV systems when the PV power generation exceeds load consumption. While this approach can effectively address overvoltage issues, it may not always be practical, as it goes against the economic interests of PV owners, who rely on maximizing the output of their facilities to realize the economic benefits of their investment. In summary, addressing overvoltage in the distribution network presents several challenges, including the need to balance economic interests with the need for a stable and reliable power supply. While solutions such as reactive power control and active power curtailment can be effective in mitigating overvoltage, they may not always be practical or feasible. As such, further research is needed to identify and develop effective and sustainable approaches to addressing this issue.

1.5 Battery energy storage system for voltage regulation

In Battery energy storage systems have gained popularity as a way to maintains voltage levels in distribution networks with a high concentration of renewable energy sources. BESS technologies offer high flexibility and fast response times, making them suitable for a variety of applications in the electric power network. In particular, BESS can be used to mitigate overvoltage by charging the batteries when voltage levels rise above standard limits. This helps to reduce the negative impact of large fluctuations in energy resources and support the stability of the power grid (Nazir et al., 2020). BESS can be used for active, reactive, or both active and reactive power regulation, as illustrated in Figure 1.3.

One of the key advantages of using BESS for voltage regulation is that it provides fast response and high accuracy compared to other methods such as capacitor banks. In addition, BESS can be used to regulate voltage at different levels of the power system, including transmission and distribution levels, making it a flexible solution for voltage regulation (Zhang et al., 2021). Another advantage of BESS is that it can provide multiple services to the power system, such as frequency regulation, peak shaving, and power quality improvement, rendering it an economically feasible approach for voltage regulation (Mousavi et al., 2019). BESS can be an effective solution for voltage regulation in distribution networks with high penetration. It provides fast response, high accuracy, and flexibility for voltage regulation at different levels of the power system. In addition, it has the capability to furnish multiple services to the power grid, making it a cost-effective solution for voltage regulation. Further research is needed to optimize the design and operation of BESS for voltage regulation in distribution networks.

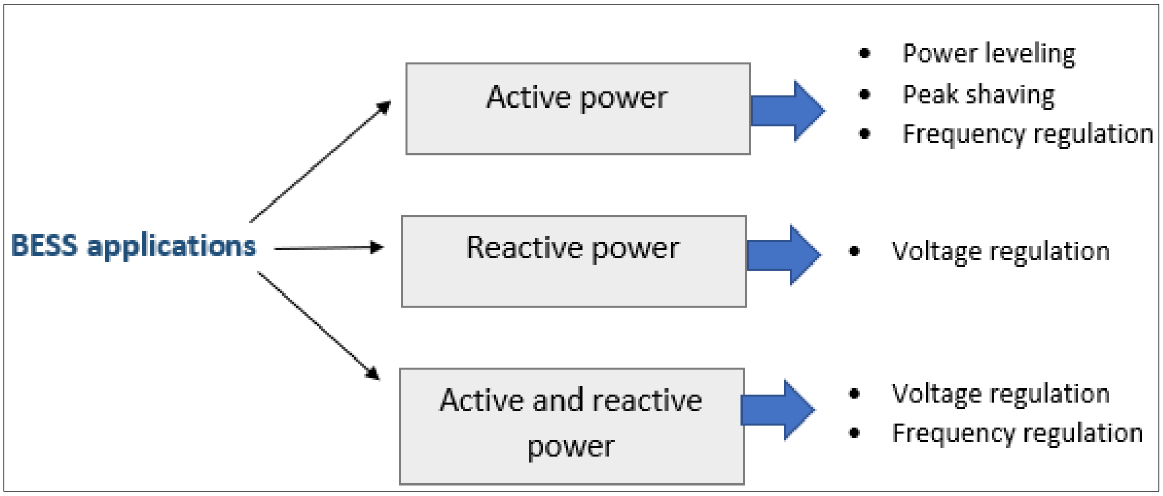

Figure 1.3 General BESS applications

BESS possess the capacity to perform a multitude of functions within distribution networks in conjunction with the extensive integration of renewable energy sources. BESS technologies have become increasingly popular due to their flexibility and fast response time for different applications in the electric power network. One of the key roles that BESS can play is in regulating the voltage output and mitigating the negative impact of large variations in energy resources, thereby supporting the power grid (Nazir et al., 2020). By charging the batteries when voltages rise beyond standard limits using storage as the extra load on the network, overvoltage can be mitigated. BESS applications can be classified as active, reactive, or both active and reactive power regulation.

In terms of active power support, BESS can enhance the mitigation of power instability, energy shifting, peak shaving, and frequency control (Alam, Muttaqi, & Sutanto, 2015). On the other hand, reactive power regulation of BESS can achieve voltage regulation and reactive power support. BESS allows for the excess energy supply to be stored and shifted to periods of high demand (Wang, Bai, Yan & Saha, 2018). It is also useful for employing voltage support and balancing the variability caused by the intermittent nature of renewable energy sources such as solar and wind power generation during a mismatch between power production and load (Tuominen, Repo & Kulmala, 2014). BESS can regulate both active and reactive power flow and provide services such as peak shaving, frequency control, and voltage regulation. It can be a suitable choice for use in applications that require high reliability in power networks. Additionally, BESS can be applied to limit load demand during high load periods in the network by charging during low load times and releasing stored energy during peak load times.

1.6 Microgrid control

A microgrid (MG) is a network of distributed energy systems, such as power generators, RESs, battery storage, and interconnected loads, that operates as a single system for exchanging power with the main grid. The central controller or energy management system controls the MG, as shown in Figure 1.4. The control strategies applied in microgrids depend on the operating mode and can effectively coordinate various types of technology and devices in the power system (Han, Ning, Yang, & Xu, 2019). Smart inverters, which act as interfaces between distributed energy resources and the grid, play a crucial role in microgrid technology, which helps to integrate renewable energy sources and provide a low-cost grid.

Microgrids have the capability to operate in two modes: grid-connected and islanded. When in grid-connected mode, the microgrid can both absorb and supply power from the grid, with a two-way flow of energy and information exchange between the distributed energy resources and the grid. The point of connection to the grid is called the point of common coupling (PCC). In island mode, the MG can only supply power to the loads, and there is no connection to the utility grid. This mode allows for the maximization of the use of renewable energy sources, but it may not be as reliable as the grid-connected mode because rapid load changes can lead to generation outages and total blackouts on the island. Maintaining a balance between generation and load demands with a high number of DER integrations is a major challenge in microgrid operation. Smart microgrids, with their smart grid features, aim to improve the reliability and stability of the power grid with efficient and clean energy.

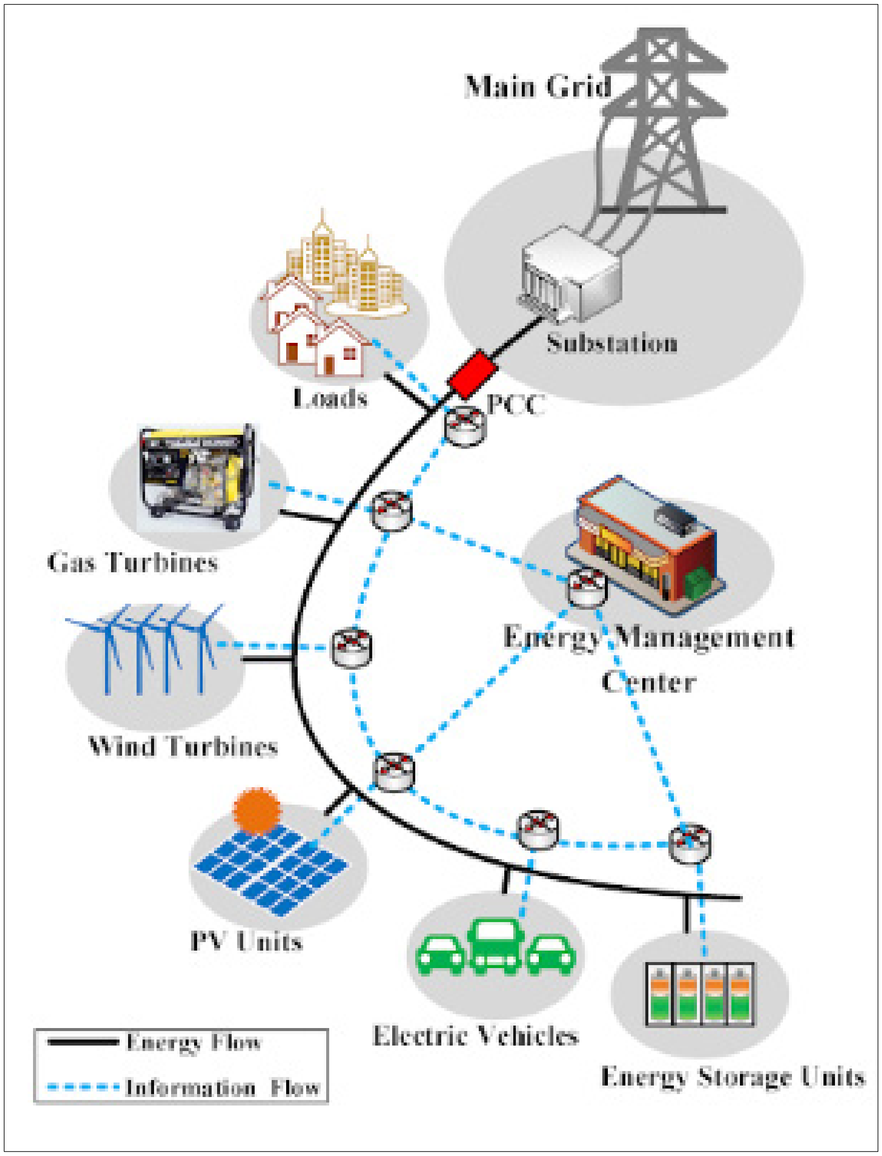

Figure 1.4 Different DERs in MG distributed control (Nazir et al., 2020)

Power systems are always at risk of disturbance, which may affect their stability. Stability analysis in MGs is a key aspect of power system design. In the event of any disturbance in the grid due to the inconsistent and unpredictable nature of RESs and any fault in the utility grid or generally upon the occurrence of abnormal grid conditions or power failure, the microgrid can be isolated from the main grid and switched to islanded mode operation. In this mode, the MG must rely on its own generation to meet the demands of local loads.

In grid-connected mode, the power deficit of the local loads can be provided by the main grid and the excess generated power can be applied to additional services in the network (Andishgar, Gholipour, & Hooshmand, 2017). However, in islanded mode, the active and reactive powers should be balanced with the local load demand to maintain the stability of the system. This requires a fast and reliable energy management system that can quickly adjust the power output of the MG's generation and storage units in response to changes in local load demand.

A fast energy management policy helps improve the functioning of an MG with a large number of DERs. However, there are some challenges in the control of MGs in terms of complexity, which can be overcome using grid support methods. The concept of an MG is proposed for controlling the entire distribution system with high integration of DERs. Accordingly, a possible method to manage this complexity is to break down the entire grid into smaller microgrids. In this control architecture, each sub-system contains only a limited amount of DER operated by the local controllers. Therefore, the MG control system operates in a fully distributed manner. In this regard, a robust control scheme is required for coordination between microgrids. This can involve the use of advanced communication and control technologies to allow the local controllers to share information and coordinate their actions in real-time, ensuring the stability and reliability of the overall MG system.

1.7 Architectures of microgrid control

The control of DERs can be categorized based on various control strategies and communication architectures, ranging from fully centralized control to decentralized and distributed control (as illustrated in Figure 2.5). The control strategies that have been proposed include centralized, hierarchical, decentralized, and distributed multi-agent control. Over the years, there has been a shift in the configuration of networks from traditional centralized systems to intelligent distributed networks comprising multiple DERs that are distributed in nature.

1.7.1 Centralized control

In a centralized control structure, all control decisions are made by a central controller that regulates the actions of all units in the network. This control architecture allows the system to consider all necessary available information and leads to improved overall performance and sufficient energy flow to the final users of the network (Cai, Chen, Duan & Yang, 2014). The centralized architecture is a powerful tool for monitoring and controlling large-scale systems, and it has been used in various fields including power systems, transportation systems, and manufacturing systems. However, it also has its drawbacks (Xu, Xiao, Wang, Pan & Wen, 2017).

One of the major concerns with a centralized control structure is the gathering and transmission of data. In a centralized system, all data must be transmitted to the central controller for processing and decision-making, which can result in privacy and security concerns. The sensitive data could be intercepted or compromised during transmission, which could lead to serious consequences. Another concern is the vulnerability to single point of failure. A centralized architecture is often used to control a single unit without communication with other parts of the system (Bidgoli & Van Cutsem, 2017), However, this approach is highly vulnerable to a single point of failure, meaning that any failure in the communication link with the central controller could shut down the entire system. This is a significant risk, particularly in critical systems such as power grids and transportation networks, where a single failure could lead to widespread disruption and damage (Vovos, Kiprakis, Wallace & Harrison, 2007).

Moreover, the integration of RESs has made the management of large-scale networks more complex, as their unpredictable variations make it a difficult task to maintain a stable and efficient energy flow. The increasing penetration of RESs leads to a heavy computational burden in information processing, making it difficult for the centralized control strategy to handle a large number of units. While centralized control architecture is a powerful tool for monitoring and controlling large-scale systems, it also has its drawbacks. Gathering data and transmission of data can result in privacy and security concerns, and it is also highly vulnerable to single point of failure. Moreover, the integration of renewable energy sources leads to a heavy computational burden making it challenging and complicated when the number of units increases.

1.7.2 Decentralized control

The decentralized or local control method is a distributed control strategy in which there is no direct communication between the various DERs participating in the system (Figure 1.5). Instead, each DER is equipped with a local controller that makes decisions based on local information and measurements (Andishgar, Gholipour, & Hooshmand, 2017). One of the key advantages of this method is that it can still maintain control of the grid even in the absence of communication or if communication networks fail. The local controllers provide fast and reliable primary control for the DERs, ensuring that the system remains stable (Morstyn, Hredzak & Agelidis, 2016). Additionally, this approach allows for the DERs to be controlled independently, which can help mitigate the negative effects of intermittent renewable generation.

However, the decentralized control method also has some limitations. It can be challenging to achieve optimal operation of the DERs as the local controllers do not have access to the overall state of the grid or the limitations of the other DERs. This can introduce challenges for power quality and overall network performance. Additionally, the use of autonomous decentralized control may not be well received by consumers, as it does not take into account external information and constraints, and as a result, may not provide the global optimal solution and overall efficiency for the entire distribution network. Furthermore, the decentralized control method has a drawback at the network level. Independent optimization of each agent or unit does not consider the overall grid state, and does not optimize the entire network as a whole. This can lead to a suboptimal solution for the whole grid and reduces the overall efficiency of the network. Obtaining a local solution for each independent agent does not necessarily provide a global optimal solution and overall efficiency for the entire distribution network.

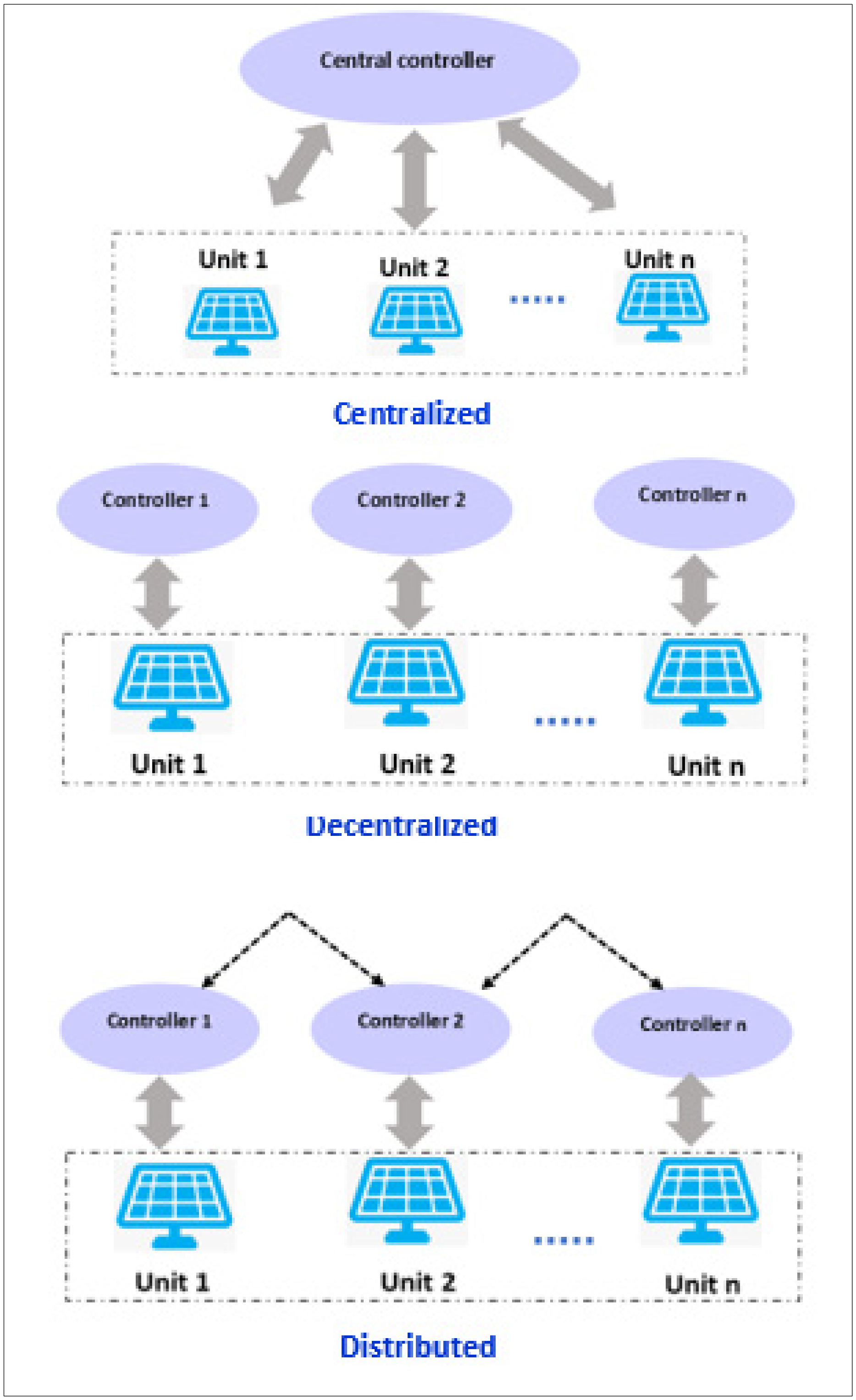

Figure 1.5 Different architectures of Microgrid Control

1.7.3 Hierarchical voltage control

A hierarchical control structure is a method of organizing the control of a power management system, such as a microgrid (MG). This type of control structure can be used in both grid-connected and islanded mode MG, and is considered a primary step towards a distributed control architecture for controlling highly penetrated distribution systems. This helps achieve overall grid control. The hierarchical control scheme consists of three levels, each with different timescales and priorities. (Figure 1.6). These levels are: primary, secondary, and tertiary. In this scheme, each level has its effect in parallel with supervising lower levels of control to achieve a stable condition in the system.

The primary level has the shortest response time and is responsible for making decisions on local power, voltage, and current control, and the coordination between secondary controllers. The secondary level has a slower response time and is responsible for supervising the primary level, and making decisions on the coordination between the primary and tertiary levels. The tertiary level has the slowest response time, and is responsible for coordinating the overall system and utilizing a communication network.

The hierarchical control scheme has the benefit of fast response to unpredictable instabilities from the primary control level, allowing it to quickly stabilize the system (Rafi, Hossain, & Lu, 2016). In this scheme, agents at different levels can communicate with each other. The primary control is at the top of the highest priority level control. Unlike other control schemes, it does not involve data exchange between units, and is focused mainly on enhancing the stability of the grid under all operating conditions. The primary level is also suitable for P-Q control and setting voltage and current reference points.

The primary level, also known as the zero level, is the first level of control in a hierarchical control system. Its main function is to accomplish local power, voltage, and current control. This level is responsible for making decisions on the coordination between secondary controllers (Tian, Xiao, Wang& Ding, 2015). These decisions are critical for maintaining the stability of the system, and as such, the primary level is designed to have the fastest response time. One key characteristic of the primary level is that it is able to operate independently of any external communication. This means that it can continue to control the system even in the event of a communication failure. This is achieved by implementing a set of control algorithms that are based on the local measurement of power, voltage, and current.

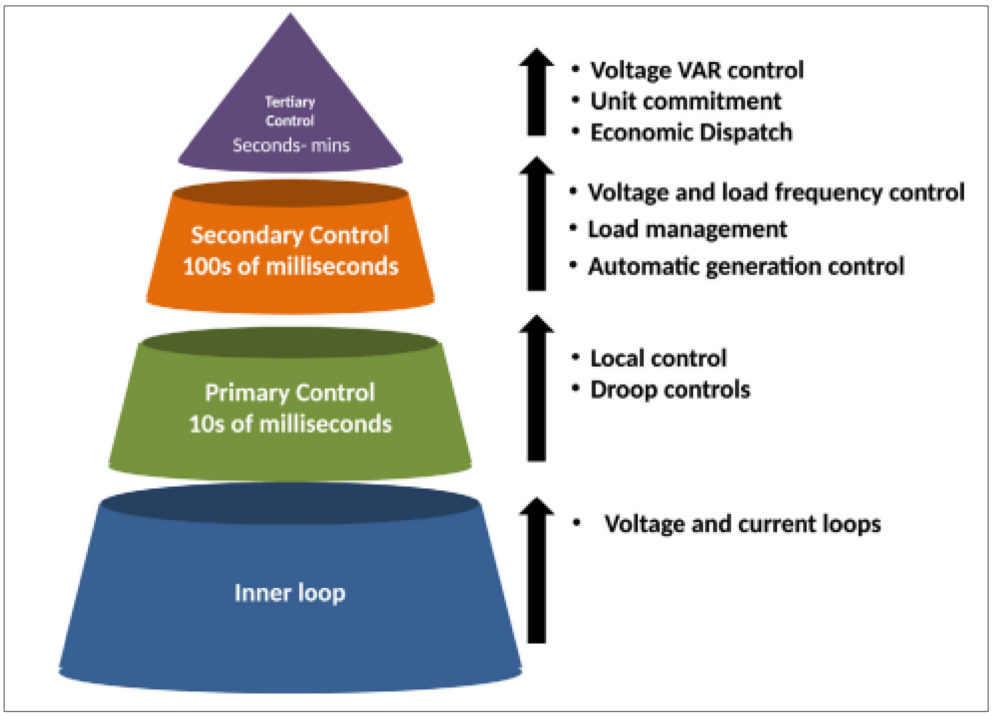

Figure 1.6 Hierarchical control (Ishaq et al., 2022)

These algorithms are designed to quickly detect and respond to any changes in the system's state. For example, if the primary level detects a sudden increase in current, it will adjust the voltage to maintain the stability of the system. In this way, the primary level acts as a protective layer, preventing the system from becoming unstable or damaged. The primary level of control in a hierarchical control system is responsible for accomplishing local power, voltage, and current control and making decisions on coordination between secondary controllers. It has the fastest response in preserving the stability of the system and works in the absence of communication.

The secondary level of control is focused on ensuring optimal power generation and distribution in the microgrid. This level is often responsible for monitoring and controlling the state of charge (SoC) of energy storage systems (ESSs), and coordination of the primary control level with other devices such as inverters. This layer has a slower dynamic response to variation, compared with the first level to justify the dynamics between both levels. The objective of the secondary controller is to enhance the power quality of the network by mitigating variations in frequency or voltage arising from RESs.

The tertiary layer is the top level is focused on longer-term planning and management of the microgrid. It can manage power interactions between DERs in a distributed manner by applying optimization functions to provide power flow regulation and optimal energy management. This level involves coordination and communication among devices, and is often responsible for scheduling and dispatching of energy resources, as well as balancing supply and demand within the microgrid. It regulates the voltage and frequency by controlling the output active and reactive powers (Mohammed, Alalwan, Taşcıkaraoğlu, & Catalão, 2022). At this level, more intelligent and efficient system operation can be achieved with a fast dynamic response. This is a communication-based level of control.

The hierarchical control scheme, while it can be useful in reducing the complexity of the system and improving the response time to disturbances in large and complex networks, it has several limitations that can make it less favorable for certain types of systems. One major limitation of the hierarchical control scheme is that it may not be able to achieve the optimal global solution in a reasonable time. The tertiary control level, which is responsible for coordinating the operations of different local DERs to achieve optimal system operation, takes the longest time to make a final decision in the system. In large and complex networks, this can make it difficult to achieve the desired level of control in a timely manner.

Another limitation is that this strategy may not be as efficient as other control strategies. The control bandwidths decrease from the primary level to the tertiary control level, which can decouple the dynamics of levels but also can increase the decision-making time and affect the overall performance of the system. This can lead to suboptimal control of the system and limit its ability to react to changes in the network. Additionally, the hierarchical control scheme can be less flexible as it is based on a centralized control approach, so in case of communication failure it could be difficult to control the system. Also, it may not be suitable for systems with a high penetration of DERs, as the coordination of so many different local controllers can be a difficult and complex task.

1.7.4 Distributed multi-agent control

A solution for the aforementioned challenges with centralized and decentralized control strategies is to design DERs in a multi-agent structure to provide distributed control. (Zhao, Dou, Ma, Zhang & Zhang, 2020). A multi-agent system is a platform with a high level of automation in the control network. In an electrical power system, an agent can refer to the DERs such as a PV system, a BESS, or an electric vehicle (EV) system that are in coordination with each other in a distributed manner. For example, a PV system can act as an agent to optimize its power generation and a BESS can act as an agent to regulate the voltage and frequency of a distribution network. Furthermore, EV systems can act as agents to participate in demand response programs. In this concept, each unit can process information independently and there is no need to have a direct connection between agents and a central controller, as each agent interacts with its neighboring agents and processes data and information through communication infrastructure (Mokhtari et al., 2013).

MAS is a robust strategy for improving the control performance compared to traditional methods and has advantages in terms of flexibility and scalability over a centralized one. Thus, the multi-agent system can be applied as a robust control system for individual MG is required to maintain local constraints and achieve global objectives. In this control scheme each agent of the system is self-organized and, in parallel, can achieve global system objectives (Zeng, Zhang, Liu, Zhuang, & Guo, 2021). An example of this application can be seen in distribution systems, where MAS can be used to coordinate distributed generators, energy storage, and load-side resources to increase the reliability, resilience and overall efficiency of the distribution grid.

The key to a successful MAS is the communication infrastructure. Local units exchange data and information through two-way communication links. The use of intelligent agents helps to advance the economical operation of distribution networks. However, designing effective communication protocols, coordinating agents' decision-making, and dealing with incomplete or uncertain information are some of the challenges that need to be addressed in order to deploy a MAS. To tackle these challenges, researchers are working on developing new algorithms for coordinating agents' decision-making, improving communication protocols and dealing with uncertain or incomplete information. This ongoing research can help to improve the performance and robustness of the system. It is important to note that the MAS approach has some trade-offs as well. For example, it can be more complex to implement and manage a MAS compared to other control approaches. Additionally, it requires a certain level of robustness and fault-tolerance, which can be hard to achieve. Therefore, it is important to carefully evaluate whether a MAS is the best control approach for a specific power system and what type of system design considerations should be taken into account.

1.8 The control scheme for the distribution grid using smart inverter

The total energy generation and consumption of the grid must always be balanced. With the high integration of DERs, maintaining voltage balance in the system is becoming challenging. Different solutions have been proposed to prevent and mitigate voltage violation issues. The simplest strategy is to improve grid infrastructure to upgrade and reinforce the distribution networks, which is very costly. Another approach is to use the OLTC transformers to modify voltage (Keane, Ochoa, Vittal, Dent & Harrison, 2010). However, this method can increase stress in the transformer (Wang, Zhang, Li, Xiao & Abdollahi, 2012). The curtailment of solar power during overvoltage periods can mitigate voltage rise, but it is not economical because it wastes PV power and affects PV owner revenues (Wang et al., 2015). Another solution is the use of battery storage to increase load demand during peak generation periods. The battery can effectively regulate the system voltage with peak power shaving.

Another approach is to overcome voltage regulation challenges by designing an intelligent control system to coordinate different DER units. To achieve this, the DERs can contribute to active control operations. In this context, using smart inverters can help support the grid by using optimization methods to achieve the goal of maximum energy utilization. Smart inverters associated with DERs have both active and reactive power adjustment functions for voltage and frequency regulation. Different voltage control algorithms can be used by smart inverters to regulate voltage such as PI controllers, droop control and optimization-based methods. These algorithms can have different advantages and disadvantages, which need to be considered when choosing the control algorithm.

Smart inverters can also offer a wide range of grid services such as voltage support, voltage sag/swell mitigation, and frequency control. These services can be provided by adjusting the active and reactive power output of the smart inverters. Additionally, the reactive power output of smart inverters can be determined based on the local active power of solar PVs, which provides more opportunities for different applications of the smart grid. With recent versions of IEEE1547 standard and distribution grid codes, solar PV inverters are now allowed to participate in the voltage regulation of the network using either or both reactive power and active power to provide new control functions (Photovoltaics & Storage, 2018).

Smart inverters can provide voltage regulation at a much more accurate and faster time scale than traditional control methods (Arora, Satsangi, Kaur, & Khanna, 2021). But it is important to consider the impact of uncertainty on smart inverter-based voltage control, such as changes in weather conditions and variations in power output from DERs. This uncertainty can be managed by using advanced control algorithms and communication protocols. Additionally, communication infrastructure is used to connect smart inverters and coordinate them for providing grid services, which is important for the overall performance of the system.

It is important to note that while smart inverters can provide many benefits for voltage regulation, it is also important to consider other solutions such as grid infrastructure upgrades, OLTC transformers, and battery storage to address voltage regulation challenges. Additionally, research in this field is still ongoing, with a focus on developing new voltage control algorithms and communication protocols, studying the economic and environmental impact of smart inverters and investigating the integration of smart inverters with other grid technologies such as energy storage systems. These research lines can help to improve the performance and reliability of smart inverter-based voltage control in future power systems.

1.9 Voltage control using active and reactive power

Many solutions have been proposed to address the negative effects of PV penetration in distribution networks. Voltage deviation problems such as voltage drop and rise issues can be mitigated by taking advantage of intelligent control functions such as the reactive power Volt-Var and Volt-Watt control techniques of smart inverters (Chathurangi, Jayatunga, Perera, Agalgaonkar, & Siyambalapitiya, 2021). Smart PV inverter control has been investigated in literature to enable maximum PV capacities. One key benefit of using active and reactive power control for voltage regulation is that it allows for greater flexibility in terms of how much PV capacity can be integrated into a distribution network.

By being able to actively manage the voltage at the point of common coupling (PCC), smart inverters can help prevent overvoltage and undervoltage issues, thereby enabling the integration of higher levels of PV penetration. Additionally, the implementation of active and reactive power control can enhance the general efficiency of distribution networks. For example, by using the Volt-Var control method, smart inverters can adjust their reactive power output based on the real-time voltage level at the PCC, which can help prevent power loss and improve the overall efficiency of the grid.

The use of active and reactive power control for voltage regulation can be deemed the most impactful aspect of current photovoltaic inverters. Smart PV inverters have the ability to regulate their active power output by monitoring the terminal voltage, and limiting it when the voltage exceeds the upper limit set by the utility. If reactive power control alone is not enough to control overvoltage, the inverters can resort to volt-watt control to reduce the grid voltage by limiting their active power output. In the volt–Watt control mode, an intelligent PV inverter can also participate in improving the voltage profile of the system during under-voltage conditions by injecting active power to the grid considering the PCC voltage (Arora, Satsangi, Kaur, & Khanna, 2021).

By supplying reactive power, the inverter performs voltage management when overvoltage or undervoltage (Kabir, Mishra, Dong & Wong, 2014). In smart Volt–Var control mode, the smart inverter can participate in voltage regulation through reactive power based on the PCC voltage and reactive power setpoints considered by the utility. Generally, to maximize the utilization of available active power generation, the Volt-Var control method is prioritized over Volt/Watt control as it does not involve power curtailment (Babu, & Khatod, 2022, March). In this regard, smart inverters can support the grid voltage drop by injecting reactive power up to its maximum. Adopting both active and reactive power control helps prevent overvoltage violation issues and improves the feeder's PV capacity.

Another important point to consider is that active and reactive power control can also help improve the stability and reliability of the distribution network. By being able to quickly and accurately respond to changes in voltage, smart inverters can help prevent power outages and other issues that can affect the overall stability of the grid. There are also many different types of smart inverter control algorithms, such as distributed control, centralized control, and hybrid control (combination of both). Each of these approaches has its own advantages and disadvantages and is more suitable for different scenarios. Furthermore, the integration of advanced forecasting and monitoring techniques like Load forecasting, solar forecasting and Wide Area Measurement Systems (WAMS) can help to improve the active power and reactive power control performance by providing real-time grid state information for better control decision making.

1.10 Optimization-based control algorithm

A large number of agents in complex power distribution systems have led to developments in smart and complex communication systems in multi-agent control schemes. Voltage control problems can be more complicated due to the uncertainties associated with renewable power resources. Weather dependency on solar energy resources will result in stability distress in the network to maintain a balance between power generation and demand. In this regard, robust optimization control methods and advanced algorithms play a significant role in supporting complex power systems' operations which motivates the employment of distributed optimization techniques using parallel algorithms.

One specific approach to addressing the challenges of distributed power generation is through the use of model predictive control (MPC) algorithms. MPC algorithms use models of the system dynamics to predict future behavior and then optimize control actions in order to achieve desired performance goals. This can be particularly useful in power systems because it allows for the consideration of both current and future conditions, and can handle constraints such as voltage and power flow limits. Another approach for distributed voltage control is through the use of consensus-based algorithms, such as the alternating direction method of multipliers (ADMM) and the distributed augmented Lagrangian method (DALM), which are based on the idea of having multiple agents agree on a common set of control actions, which can be particularly useful in large-scale, decentralized systems.

Smart inverters are an important tool for distributed voltage control, as they allow for the integration of distributed energy resources into the power system in a controllable and predictable manner. Modern PV inverters have the capability of both active and reactive power control, and they can also regulate voltage and frequency. The communication infrastructure is also important to consider, as it allows for real-time monitoring and control of the voltage and power in the grid, in addition to the current state of charge of the energy storage systems and the power of renewable resources. This improves voltage and frequency regulation, and allows for peak shaving.

Applying these features to smart inverters can effectively influence the voltage profiles of the network. Distributed coordinated voltage control is an alternative approach to solving the challenges of centralized control schemes. The MAS-based control scheme is a robust technique for the voltage regulation of DERs. MAS control has been studied for several power system applications to enable fully distributed control systems. Distributed voltage control algorithms in the literature are mostly based on iterative constraint optimization methods. Voltage control problems can be modeled as optimization problems subject to constraints aimed to determine the optimal objectives. The goal of the function is to reduce losses and minimize changes in voltage levels within the network. Iterative algorithms have been implemented to realize different objective functions. In this regard, innovative control algorithms have been developed that enable DERs to coordinate to achieve optimal operation in grid voltage control. However, the integration and complexity of these algorithms and communication infrastructure is a challenge that is currently being addressed by researchers and companies creating solutions that can be integrated into utility systems and are able to handle the increasing complexity of the power grid.

1.11 ADMM-based control algorithm

Distributed constraint control method based on optimization algorithms, is used in voltage regulation. The nonconvex problems can be solved efficiently by convex relaxation methods using optimization tools. Different types of distributed algorithms for power and voltage regulation vary in their performance, computational design, and interaction structure. The iterative algorithms are mainly based on the Dual Decomposition (DD) method and the Alternating Direction Method of Multipliers (ADMM) with different applications. These mathematical control methods take advantage of the parallelization of the problem to analyze complex and large power systems.

In this thesis, we focus on developing ADMM for distributed energy management. In recent years, the ADMM has been widely used in energy management with a wide range of applications for distributed optimization problems (He, Wu, Liu & Shahidehpour, 2016). This iterative algorithm can be implemented in a fully distributed manner without a central controller. The ADMM was originally formed from a problem separated into two subproblems and consists in solving each sub-problem in parallel. In this multiagent control algorithm, each agent represents an actor in the system and, each decision maker solves its local optimization problem considering the global objective in the network in an iterative decomposition manner. Agents may couple with each other via coupling constraints. The neighbouring variables are the objective function and constraints of the other sub-problem (Nguyen, et al., 2020). These variables allow the updating of the multipliers. Other agents can cooperate to support the grid if a single agent fails. The coordination and interoperation between agents in the multi-agent system allow DERs to participate in voltage control using the optimal capabilities of their active and reactive power. Using ADMM, the entire grid optimization problem can be broken down into multiple subproblems that are handled by local computation at agents in a relatively small number of iterations (Zhong, et al., 2019). The point of common coupling (PCC) is a gate to link the DERs. By reducing the dependency on a central grid, DERs can cooperatively maintain their demand-supply balance.

An important aspect to consider is the relationship between the convergence rate of ADMM and the choice of penalty parameter. The penalty parameter controls the trade-off between the accuracy of the solution and the speed of convergence, and choosing an appropriate value can have a big impact on the performance of the algorithm. Moreover, ADMM can handle a wide range of optimization problems, including both convex and nonconvex problems, this makes it a versatile tool for solving a variety of problems in power systems, such as optimal power flow and economic dispatch. In addition, ADMM can also handle inequality constraints by introducing slack variables and multipliers, which allow the problem to be transformed into a problem with only equality constraints. The algorithm's ability to handle "coupling constraints" which constrains the problem by linking different optimization variables and constraints between agents, this linking allows the neighbouring variables to be communicated between agents.

ADMM can also be extended to handle time-varying optimization problems, which can be useful for dealing with dynamic systems like power systems. However, it's important to note that the algorithm is sensitive to the choice of initial conditions, and choosing a good initial point, or using a warm-start strategy can improve the efficiency of the algorithm. Furthermore, ADMM is not always the best choice for every problem, in cases where the problem has a highly structured structure, other specialized algorithms such as primal-dual methods may be more efficient. It's important to weigh the trade-offs and select the appropriate algorithm for the problem at hand.

CHAPTER 2

ADMM –BASED MULTI-OBJECTIVE CONTROL FOR MITIGATING THE IMPACT OF HIGH PENETRATION PV INTEGRATION IN DISTRIBUTION SYSTEMS

The integration of significant amounts of renewable energy sources into current distribution networks can present difficulties in maintaining voltage stability. In this chapter, a multi-agent distributed voltage control strategy based on the Proximal Jacobian Alternating Direction Method of Multipliers (PJ-ADMM) is utilized for distribution power systems with high penetration of PV resources. The distributed optimization technique utilizes the augmented Lagrangian method, breaking down the optimization issue into multiple smaller problems and resolving them simultaneously. The active and reactive power outputs of all PVs are optimized locally through smart inverters to mitigate the voltage violation problem as well as keep the bus voltages at all agents within the feasible limits. The uncertainties associated with PVs are considered in different scenarios. Finally, the proposed method is conducted on a modified IEEE 13-bus system with four solar PV units in MATLAB/Simulink to validate the effectiveness of the method under different scenarios. A comparison of the results of the voltage profiles with and without the control algorithm demonstrated the robustness and fast convergence of the proposed approach.

2.1 Introduction

The demand for distributed energy resources has significantly increased. Distributed energy resources mostly include renewable energy sources. Solar photovoltaic power is a promising renewable energy source in the global market. (Tewari, Mohapatra, & Anand, 2020). Over the last decade, the development of PV sector technology has rapidly increased worldwide as a result of its technical, economic, and environmental benefits (Zhao & Ding,2017). Driven by efforts to deal with climate change, there has been a growth in PV deployment and this development brings several advantages for maintaining clean and sustainable energy. However, the penetration of PV resources has caused various challenges in the performance of low-voltage distribution networks, one of which is the voltage violation issue due to the mismatch between loads and solar PV generation (Li, Yang, Tang, Yu & Li, 2021). Since distribution networks traditionally have been designed for unidirectional power flows, high penetration of PV systems can negatively affect the voltage stability of the networks caused by reverse power flow during periods with excessive solar generation. Moreover, uncertainties associated with the intermittent nature of PVs lead to additional challenges in balancing the power and voltage profiles of the system (Wang et al., 2018). Hence, it is important to maintain network voltages within an acceptable range. In North America, the voltage at the end user is required to be maintained within the range of [0.95, 1.05] p.u. (considering ±5% of nominal voltages) according to the ANSI voltage standards (Tahir, 2019).

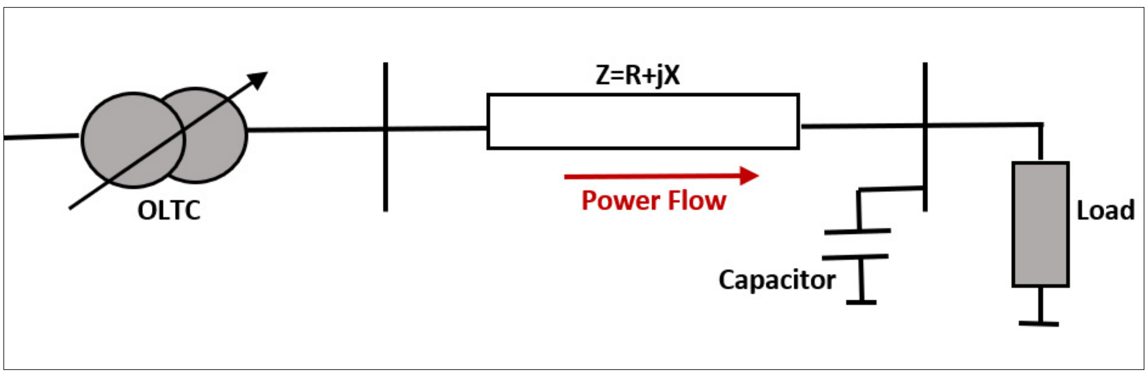

Figure 2.1 Simple passive distribution system

Distribution systems typically are passive means that they are just fed from a distribution substation with one or more primary feeders with one direction power flow from a supply to users (Tahir, 2019). Figure 2.1 shows a typical one-way distribution system. Various methods have been proposed to prevent and overcome voltage problems in distribution networks, such as upgrading the grid by installing more infrastructure, such as cables, which is usually costly (Mahmud & Zahedi,2016). On-load tap changers (OLTC), Step Voltage Regulators, and Capacitor Banks are some conventional voltage regulation devices in passive power distribution systems (Ravindra et al., 2012) which are not sufficiently fast to regulate the voltage in highly penetrated networks (Safavizadeh, Yousefi, & Karshenas 2017). PV power curtailment during high-power generation is an effective strategy in this context. However, active power curtailment causes a loss of PV energy capacity, which is against the decarbonizing goals (Zhang et al., 2019).

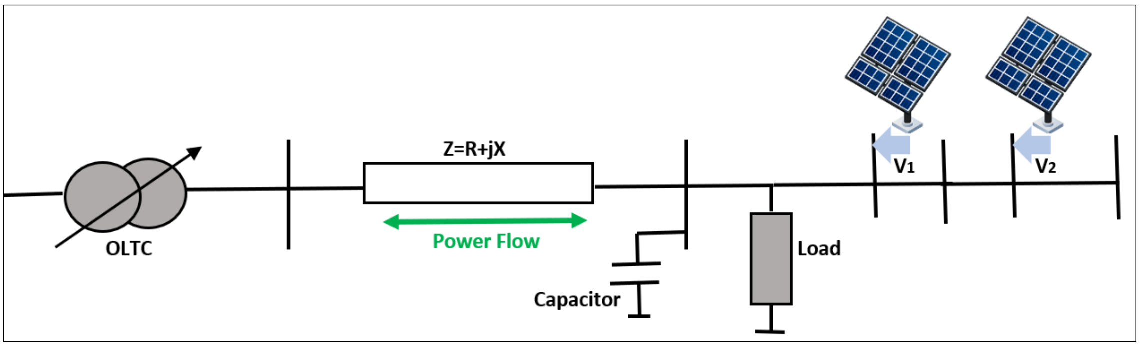

Figure 2.2 Simple active distribution system

The integration of renewable energy sources in the distribution system affects the control configuration and operation of the power system. The high integration of RESs into the distribution system has several effects on the operation of networks. In this regard, a solution can actively control the active and reactive power capability of PV inverters for voltage regulation. An active distribution system is the more recent structure of the distribution system that can include both centralized and distributed energy sources. The structure of the active distribution system is presented in Figure 2.2.

With the current standard of the IEEE 1547 standard (Photovoltaics & Storage, 2009). intelligent PV inverters can provide more features in grid voltage support through their active power control (Volt-Watt) and reactive power control (Volt-VAr) functions (Gush, Kim, Admasie, Kim & Song, 2021). The reactive power control function of intelligent inverters can support the voltage by providing or using reactive power. Smart inverters can also regulate voltage by curtailing active power (Gush, Kim, Admasie, Kim & Song, 2021), However, curtailing the active power affects PV owner revenue by limiting the solar PV power capacity. These advanced features provide more flexibility in voltage support and enable smart inverters to play a more active role in maintaining the stability of the distribution grid. Additionally, smart inverters can have communication lines that allow them to receive reference active and reactive power from the grid operator, which can be used to further optimize and coordinate their output to support the grid voltage.

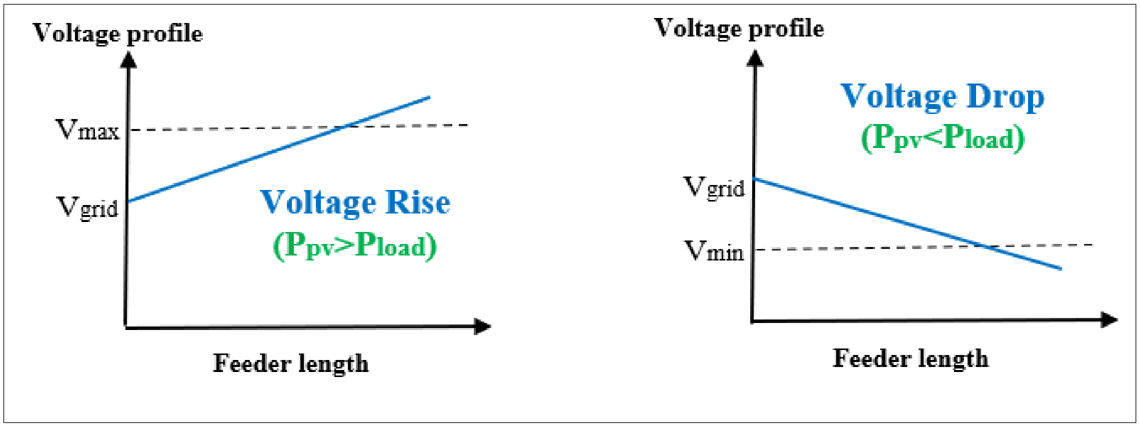

Figure 2.3 Voltage profiles of distribution network. (a)Voltage rise; (b) Voltage drop

Figures 2.3(a) and 2.3(b) show the PV highest generation period (voltage rise) and (b) the peak load period (voltage drop) respectively. The direction of power flow can lead to an increase or decrease in the voltage profile of systems. The voltage profiles of the network may decrease or increase based on power flow direction in peak PV generation or high load periods. When the voltage of the grid violates the upper and under limits, control functions will be active in all participating agents to improve voltage profiles of the system. Violation of standard constraints can cause negative effects on the different parts of the distribution network (Zeraati, Golshan & Guerrero 2016). Using optimization-based control methods using intelligent inverters leads to faster regulation compared to regulation devices such as capacitors.

Different techniques have been studied in the literature for controlling the voltage in the distribution network (Kumar, Gandhi, Rodríguez-Gallegos& Srinivasan, 2020), which is categorized based on their architectures from highly centralized coordination to fully distributed coordination: centralized, decentralized, and distributed multi-agent systems (MAS) control (Antoniadou-Plytaria, Kouveliotis-Lysikatos, Georgilakis, & Hatziargyriou, 2017). A centralized control scheme with multiple DERs typically addresses challenges in terms of scalability. In the centralized control method, a central controller is required to regulate the voltage profile of the network. However, centralized control structures face communication challenges in large-scale networks. Moreover, this control architecture can result in single-point failures (Gerdroodbari, Razzaghi, & Shahnia, 2021). A centralized control method was formulated for a distribution network (Wang et al., 2015) to control BESS, overcome the voltage rise issue, and reduce power costs. However, owing to a lack of coordination among agents in case of failure, other agents do not support the system. A fully centralized control scheme operates as a master-slave controller for DERs when the energy resources are considered slave controllers that follow the objectives and constraints of the master unit. However, this method of control can be the risk of an overall shutdown in the case of disconnection in the communication network.

The second category is the decentralized control method. Each unit processes local data in this technique without interacting with the other units (Bahramipanah, Cherkaoui & Paolone, 2016). [16]. Therefore, this scheme cannot achieve optimal management. The authors in (Bazrafshan & Gatsis, 2016). developed a decentralized power control scheme for PV units that uses only their local computations to minimize the total cost of power losses and results in closed-form updates per node. Coordinated control for PV and BES based on a decentralized structure was implemented in (Von Appen, Stetz, Braun, & Schmiegel, 2014) to improve overvoltage. However, this scheme does not provide optimal management. A decentralized control framework is presented in (Nikmehr, 2020). for a multi-objective microgrid in a distribution system; uncertain supply and demand parameters were modeled to address the uncertainty conditions using a robust optimization method. However, the network's constraints were not considered in the proposed scheme.

Recently, distributed control structures have attracted increasing attention. Due to avoiding the above-mentioned challenges associated with centralized and local schemes, the architecture of the power system is shifting towards a fully distributed MAS-based control structure (Zhang et al., 2019). Distributed voltage control techniques can be formulated as a distributed optimization problem (Almasalma, Claeys & Deconinck, 2019), which have the potential to reach several advantages that optimization algorithms offer in comparison to traditional control schemes such as a globally optimal solution. Moreover, this control method has a good potential for use in the high penetration of renewable systems with several agents, as they are robust and scalable. The distributed voltage control system operates without a central controller. In this method, each decision-maker is called an agent, and all independent agents are responsible for controlling its local resources and participating in data sharing in parallel with other agents (Liu, Guo, Lu, Chai, Gao& Xu, 2019). In this control method, failure in a unit will never cause a global blackout in the network. Reference (Molzahn et al., 2017) is a survey on different optimization control algorithms for power systems.

Distributed control algorithms are mainly designed based on an iterative theoretical framework, such as the alternating direction method of multipliers (ADMM), which can extract a set of optimal solutions for the optimal regulation of multiple objectives. In this method, a complex optimization problem decomposes into several sub-problems by applying the theory of Lagrangian multipliers and duality to compute a desirable solution (Rajaei, Fattaheian-Dehkordi, Fotuhi-Firuzabad, Moeini-Aghtaie, & Lehtonen 2021). The decomposed subproblems enable fast parallel computations. To this aim, robust optimization control algorithms have been developed with potential scalability advantages to coordinate the smart inverters for participating in voltage control using their active and reactive power control capabilities (Almasalma, Engels & Deconinck, 2017).

The standard ADMM is mainly applied as an efficient solver for optimization problems with several independent objective functions (Wang, Su, Chen, Li & Mei, 2019). A robust distributed multi-objective control technique for grid support was proposed in (Rajaei, Fattaheian-Dehkordi, Fotuhi-Firuzabad, Moeini-Aghtaie, & Lehtonen 2021), which addresses the very worst scenarios associated with the uncertainties of units using the ADMM algorithm. The authors of (Liu, Li, Gooi, Jian, Xin, Jiang & Pan, 2017) developed a fully optimization-based distributed technique for managing local resources in multiple interconnected microgrids. In this method, the uncertainty penalties in the system can be determined by each unit to optimize the operation of the grid.

Reference (Chen & Yang, 2017) implemented the ADMM algorithm to decompose a complex nonconvex problem into several subproblems to overcome the computational complications caused by the high penetration of DERs in an extensive network. Distributed voltage control based on the ADMM was introduced in (Zheng, Wu, Zhang, Sun, & Liu, 2015) with reactive power management, considering the optimal global solution for a nonconvex system. Reference (Kargarian et al., 2016) compared the performance of the ADMM algorithm in tests related to the optimal power flow with other decomposition algorithms. In (Huang et al., 2019), a distributed control scheme for voltage regulation based on the consensus ADMM was developed to control the voltage in wind turbines using reactive power. In (Magnússon, Weeraddana, & Fischione, 2015), an ADMM-based method was proposed to solve the power flow in a distributed system. The technology behind smart inverters actively supports the grid and handles voltage violations during undervoltage and overvoltage periods by supplying or absorbing reactive power (Liu, Shi, & Zhu,2017). Despite the advantages of the ADMM-based algorithm, its implementation has some challenges owing to its complexity. Another challenge in iterative optimization algorithms is to solve the problem within a appropriate period time, which can be achieved by reducing the number of iterations (Ananduta, Ocampo-Martinez & Nedić, 2021).

A Jacobian-based ADMM algorithm was developed in (Almasalma, Claeys & Deconinck, 2019) for voltage control by optimizing the active and reactive power support through peer-to-peer communication protocols in the absence of the master controller. The peer-to-peer communication method is a robust control system in which a failure in a controller does not lead to an overall impact on the system (Almasalma, Engels & Deconinck, 2017). The communication layers were distributed between the initial control parameters and Lagrangian multipliers between the control units. In this context, a MAS-based optimization scheme can be formulated to improve the voltage profile of the network in parallel coordination scheme using the smart inverter. This method aims to optimize the PV inverter outputs in the MAS concept to regulate the voltage within a standard limit at any node in the distribution network by utilizing reactive power support and minimum active power curtailment.

(Manshadi, Liu, Khodayar, Wang & Dai, 2019) proposed a convex relaxation framework as a distributed solution for the power flow problem using Jacobi-proximal alternating direction method of multipliers (JP-ADMM) is implemented to efficiently solve the problem with fast convergence using the second order moment relaxations provides a tighter relaxation in complex computation. The scalability of the proposed algorithm is addressed through case studies with thousands of buses. (Olivella-Rosell et al., 2020) presents the use of a distributed power optimization technique, the JP-ADMM algorithm, to optimize the allocation of charging services for Plug-in Electric Vehicles (PEVs) and capacity for large-scale PEV charging in power distribution systems with high PEV penetration. a novel optimization approach for large-scale distributed battery units is presented in (Li, Gao, Chen, Zhao & Shen, 2019), which utilizes a modified version of the PJ-ADMM algorithm to optimize cost and provide flexibility services. The proposed method is demonstrated to generate optimal, real-time scalable solutions through a case study, which are equivalent to centralized optimization, and computed faster.

This chapter presents a distributed voltage control method based on Proximal Jacobian ADMM (PJ-ADMM) (Deng, Lai, Peng & Yin, 2017) as an optimization algorithm in the concept of multi-agent control technique in which the active and reactive power outputs of PVs are controlled via smart inverters to maintain the optimal voltage within feasible bands in the parallel scheme. Applying additional penalty factors gives rise to faster voltage convergence. The primary advantage of using the PJ-ADMM algorithm is its ability to solve large-scale optimization problems with the cooperation of multiple agents in a parallel and distributed manner. The PJ-ADMM algorithm can effectively handle both convex and non-convex problems with general constraints, and it has been shown to have fast convergence and good scalability. We chose to use PJ-ADMM in this study because it can address the multi-objective and multi-agent nature of the proposed optimization problem in a distributed manner and reduce the communication burden among agents. The use of smart inverters allows for a distributed and parallelized approach to voltage control, as each inverter can work on its own subproblem independently and in parallel with the other inverters.

The JP-ADMM algorithm is applied to the control loop of the PV inverter through the grid voltage support function. The distributed optimization algorithm iterates over an order and the proximal penalization functions which are updated in parallel till the convergence is preserved. To the best of our knowledge, employing a parallel optimization method based on PJ-ADMM with prioritizing the use of the reactive power for voltage control through smart inverters considering uncertainties of high penetration of PV systems has not been investigated previously. The PJ-ADMM framework is proposed to minimize power loss by using PV inverters which enable it to solve multi-objective problems with parallel execution features and fast convergence. In this method, each agent optimizes its own sub-problem. The proposed method can currently be applied to reactive power support for regulating voltage during high voltage periods without active power curtailment and during night times. The main contributions of this session are as follows: 1) The possibility for improving the voltage profiles during worst-case scenarios in terms of PV generation and load demand with either active power or reactive power or both 2) minimizing the active power curtailment where PVIs greatly provide voltage support during overvoltage conditions with reactive power contributions of PVIs in a fully distributed manner.

2.2 Methodology

2.2.1 Problem formulation

Figure 2.4 shows the basic structure of a distribution system with several agents which are connected to a load. The objective function of the voltage control problem based on a centralized constraint control system is formulated in equation (2.1). It is the sum of the quadratic cost functions which aims to diminish the costs of variations in active power (P) and reactive power (Q) of PV inverters at time step t. Each inverter must locally satisfy the voltage constraint equation (2.2). To solve this optimization problem, $\mathrm{V}^{\mathrm{min}}$ and $\mathrm{V}^{\mathrm{max}}$ denote the lower and higher voltage boundaries of the n^{th} PV inverter, respectively. $\mathrm{V}_{\mathrm{n}}^{\mathrm{t}}$ represents the n^{th} inverter voltage magnitude at the PCC after applying $\Delta\mathrm{P}_{\mathrm{n}}^{(\mathrm{t})}$ and $\Delta\mathrm{Q}_{\mathrm{n}}^{(\mathrm{t})}$.

$$\text{Minimize}_{\Delta P,\Delta Q} \sum_{n\in N} F_n^P (\Delta P_n^{(t)})^2 + F_n^Q (\Delta Q_n^{(t)})^2 \tag{2.1}$$

$$\text{Subject to: } \forall n \in N \qquad V^{min} \le V_n^t \le V^{max} \tag{2.2}$$

Where N is the set of PV inverters installed in the voltage control of the system, and n is the number of contributed inverters. The variables $\Delta P_n^{(t)}$ and $\Delta Q_n^{(t)}$ refer to the changes in the active and reactive powers of the n^{th} inverter, respectively. $F_n^P(\Delta P_n^{(t)})^2$ and $F_n^Q (\Delta Q_n^{(t)})^2$ are the cost functions associated with changes in the active and reactive powers of the inverters, respectively. F_n^P and F_n^Q are constant penalty factors that denote the control of participation, P and Q, respectively. These factors priorities the control actions, where F_n^Q should be lower than F_n^P . The cost of reactive power compensation is lower compared to reducing the active power output.

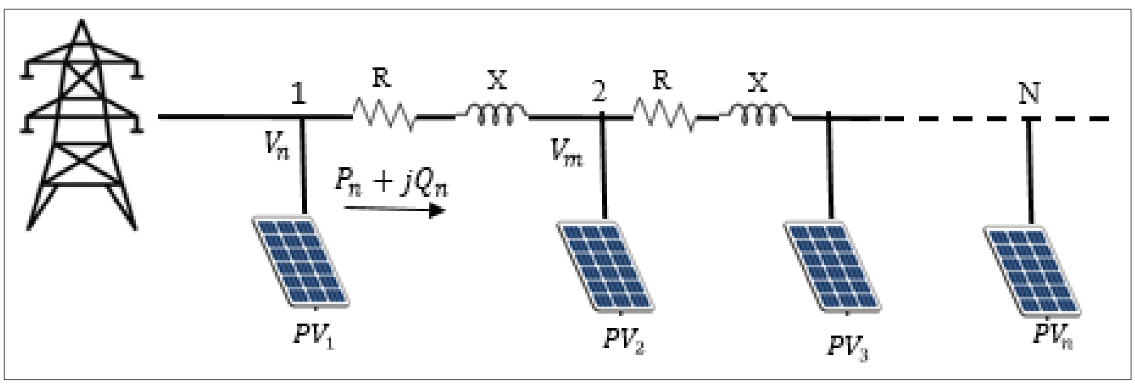

Figure 2.4 The basic structure of a distribution system with multiple PV agents.

Constraints equation (2.3) and (2.4) on local variables $\Delta P_n^{(t)}$ and $\Delta Q_n^{(t)}$ are considered for model (2.1) to maintain the lower and upper limits on the voltage magnitude of the units and to constrain the amount of exchanged power between the nodes. The active power curtailment factor is denoted as C_u which determines the cutting percentage. $(P_n^{PV})^t$ is the power generated by the n^{th} inverter. The apparent power is denoted as S_n. The maximum reactive power curtailment can be calculated through equation (2.5):

$$(-C_u)(P_i^{PV})^{(t)} \leq \Delta P_n^{(t)} \leq 0 \tag{2.3}$$

$$-(\Delta Q_n^{(max)})^{(t)} \leq \Delta Q_n^{(t)} \leq (\Delta Q_n^{(max)})^{(t)} \tag{2.4}$$

$$(\Delta Q_n^{(max)})^{(t)} = \sqrt{S_n^2 - ((P_n^{PV})^t + \Delta P_n^{(t)})^2} \tag{2.5}$$

$$f\,(V_n^t, \Delta P_n^{(t)}, \Delta P_n^{(t)}) = 0 \tag{2.6}$$

where constraint equation (2.6) denotes the nonlinear relation between the voltage magnitude and the active and reactive powers as input variables in each inverter, which causes nonconvex power flow problems (Deng, Lai, Peng & Yin, 2017). Once the system controller detects any voltage violation, the centralized control system will estimate the active and reactive power changes required to overcome the voltage rise or drop due to restore the voltage to the limit. In this regard, the optimization problem equation (2.1)–(2.6) solves by a centralized design as Figure 2.5. by gathering variables as inputs, such as solar power generation and bus voltage, to solve the problem, and a central optimizer minimizes the total change in active/reactive power in each inverter to achieve the optimal control in the system.

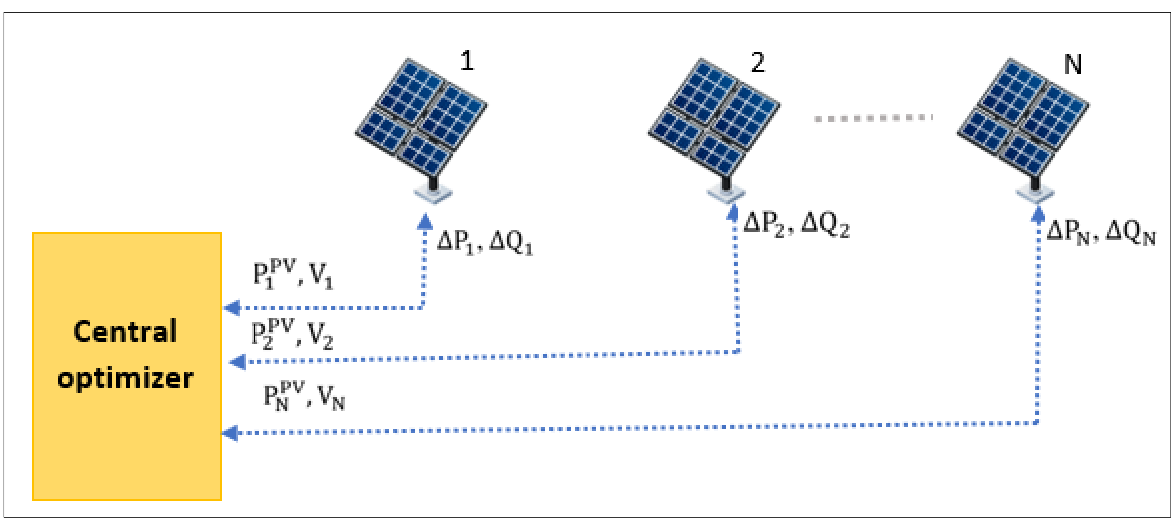

Figure 2.5 Centralized voltage control with two-way communication system

The central controller then shares the new set points with all participating agents to support the grid and regulate the voltage profile of the system within the accepted ranges. However, the major challenge of this method is that the system is always at risk of a single point of failure. A central coordinator is required to collect variables from each unit to regulate an optimal set point for supporting the grid. In this scheme, a robust communication system is also required to exchange information between the agents participating in the system. Therefore, a solution to the challenges above is to use a method to split the centralized control system into a multi-block control system that can improve the voltage profiles in parallel using MAS-based algorithms. The optimization problem doesn't take into account power losses. However, further constraints can be added to the formulation to decrease network losses through the utilization of storage, which will be covered in the following chapter.

2.2.2 Voltage sensitivity

In the distribution network, variations in power injection can make violations in system voltage. The non-convex AC problem can cause difficulties in controlling distributed control optimization. linearizing power flow equations can be a solution to avoid this problem which has been used in many studies (Lu & Chu, 2017), (Lofberg, 2004). Different methods can be used to compute the voltage sensitivities. Such as applying perturbations in power to determine the voltage sensitivities and measure the voltage variations. The linearization of all voltage magnitudes using voltage sensitivities can help formulate a linear relationship between the input parameters to solve the power flow problem in the convex relaxed form in the distributed scheme (Huang et al., 2019). The relationship between the bus voltage magnitude and small variations in the active and reactive powers for a set of inverters can be calculated using the voltage sensitivities as equation (2.7):

$$V_m^{(k)} \approx (V_m^{(M)})^{K-1} + \sum_{n \in N} \frac{\partial V_m}{\partial P_n} \ \Delta P_n^{(k)} + \frac{\partial V_m}{\partial Q_n} \ \Delta Q_n^{(k)} \tag{2.7}$$

where $\Delta P_n^{(k)}$ and $\Delta Q_n^{(k)}$ denote the deviations in the active and reactive powers in each iteration k. $(V_m^{(M)})^{K-1}$ denotes the controlled voltage measured in the previous iteration. $\frac{\partial V_m}{\partial P_n}$ and $\frac{\partial V_m}{\partial Q_n}$ are the voltage sensitivity coefficient matrices updated at each node in each iteration (Guo, Wu, Gao, Huang, Zhou & Li, 2019). These parameters express the influence of changes in variables P and Q on the voltage control of the inverters and can be written in simplified forms $\frac{\partial V_m}{\partial P_n} \approx V_{nm}^{(P)}$ and $\frac{\partial V_m}{\partial Q_n} \approx V_{nm}^{(Q)}$. Sensitivity coefficients are used for estimation of the variations of voltages and phase angles in the PV control system. The topology of the grid and the information about the line impedances can be used to compute the voltage sensitivity coefficients. For a set of inverters, a linear voltage model can be expressed using the voltage sensitivity coefficients ($V_{nm}^{(P)}$ and $V_{nm}^{(Q)}$), which represent the effect of active and reactive power, respectively, on the controlled voltage.

2.2.3 ADMM method

In this context, the alternating direction method of multipliers (ADMM) can be an effective approach for optimal management of distribution system. The ADMM algorithm was originally a system with two blocks, which has been widely applied to solve distributed problems in different applications. However, it is desirable to partition the centralized optimization problem into multiple agents that allow parallel computing to solve problems in large-scale distribution systems (Kou et al., 2020). In general, a convex optimization problem can be expressed as follows (Rajaei, Fattaheian-Dehkordi, Fotuhi-Firuzabad, Moeini-Aghtaie, & Lehtonen 2021):

$$Min\ A(x) + B(z) \tag{2.8}$$

$$Subject\ to:\ ax\ +\ bz\ = c \tag{2.9}$$

where A(x) and B(z) are independent objectives and separable considering variables x and z which can be decomposed into x-update and z-update steps in each agent. The ADMM model can be formulated by equation (2.10) to solve the optimization problem using the augmented

Lagrangian function with penalty terms which can be carried out in parallel (Li, Liu, Liang & Shen, 2020), where ρ the augmented penalty factor on the constraints is a constant positive factor (Rajaei, Fattaheian-Dehkordi, Fotuhi-Firuzabad, Moeini-Aghtaie, & Lehtonen 2021).

$$L_{\rho}^{(x,z,\lambda)} = A(x) + B(z) + \lambda^{T}\ (ax\ +\ bz\ - c) + \frac{\rho}{2}\ ||\ ax\ +\ b -\ c||_2^2 \tag{2.10}$$

Finally, the iterative ADMM model of equation (2.8) is derived in (2.11)-(2.13) when the variables are updated in each iteration k (Rajaei, Fattaheian-Dehkordi, Fotuhi-Firuzabad, Moeini-Aghtaie, & Lehtonen 2021), and the augmented Lagrangian is minimized over X and Z, with a dual update of λ.

$$x^{k+1} = arg\ min\ L_{\rho}\ \ (x, z^{k},\ \lambda^{k}) \tag{2.11}$$

$$z^{k+1} = arg\ min\ L_{\rho}\ \ \ (x^{k}, z,\ \lambda^{k}) \tag{2.12}$$

$$\lambda^{k+1} = \lambda^{k} + \rho(ax^{k+1}, bz^{k+1} - c) \tag{2.13}$$

Although the standard ADMM performs well in solving convex models, its performance in terms of convergence is insufficient for non-convex problems. In this regard, the multi-block ADMM can be advanced to the proximal Jacobian ADMM to relax the coupling between the functions and help decompose the centralized problem into several minor problems (Ananduta, Ocampo-Martinez & Nedić, 2021) , (Almasalma, & Deconinck,2020). This study proposes a MAS-based distributed control system for voltage regulation using a distributed optimization algorithm. Applying the PJ-ADMM approach, the centralized problem can be break down into subproblems that can be updated in parallel to be solved by each agent with fast convergence iteratively (Lu & Chu, 2017).

The two-block ADMM can be expanded to multi-block Gauss-Seidel ADMM and multi-block Jacobi ADMM (Almasalma, Claeys & Deconinck, 2019). The Gauss-Seidel ADMM is a sequential algorithm and cannot guarantee convergence. All these characteristics make it an inefficient algorithm for controlling large-scale systems. On the other hand, in the Jacobi ADMM algorithm, the agents can be updated in parallel. Although the convergence rate is too slow it is guaranteed. In this model, each agent needs to consider its local and global variables. Also, global variables should be considered to meet sub-problem objectives conducted by neighbor agents. In this thesis, we focus on a distributed optimization algorithm—Proximal Jacobi ADMM– for solving a convex optimization problem with multiple agents, where the problem formulation equation (2.3) -(2.6), can be decomposed into several subproblems to be solved in parallel. Using the PJ-ADMM the voltage problem can be regulated within the required limits with fast convergence.

2.2.4 PJ-ADMM algorithm

The PJ-ADMM is chosen to solve the above-mentioned optimization problem because of its robustness and high performance in determining optimal values compared to other ADMM-based algorithms. The original proximal Jacobian ADMM methodology was adapted from (Deng, Lai, Peng & Yin, 2017). The centralized objective function in equation (2.1) can be decomposed into the sum of several convex functions related to each PV unit considering the local constraints. In each iteration, the variables ΔP and ΔQ are updated in parallel and agents exchange their Lagrangian multipliers with neighbor agents.

Adding proximal terms such as penalty factors helps speed up the convergence rate. Equation (2.15) is the proximal augmented Lagrangian of the equation (2.1) after adding proximal terms on each sub-problem and considering the initial limits on variables $\mathrm{V}_{\mathrm{n}}^{\mathrm{k}}$, $\Delta\mathrm{P}_{\mathrm{n}}^{(\mathrm{k})}$and, $\Delta\mathrm{Q}_{\mathrm{n}}^{(\mathrm{k})}$ .The detailed formulation of the proposed method is given as follows:

$$f_n^k = F_n^P(\Delta P_n^{(k)})^2 + F_n^Q\,(\Delta Q_n^{(k)})^2 \tag{2.14}$$

$$\mathcal{L}_\rho(\Delta P_n^{(k)}, \Delta Q_n^{(k)}, (\lambda_n^{max})^{(k-1)}, (\lambda_n^{min})^{(k-1)})$$
$$= \Sigma(f_n^k + (\lambda_n^{max})^{(k-1)}(V_n^k - V^{max})$$
$$+ (\lambda_n^{min})^{(k-1)}\left(-V_n^k + V^{min}\right) + \frac{\rho_n}{2} max\,(0, (V_n^k - V^{max}))^2$$
$$+ \frac{\rho_n}{2} max\,(0, \left(-V_n^k + V^{min}\right))^2 + \frac{\tau_n}{2}\,(\Delta P_n^{(k)} - (\Delta P_n^c)^{(k-1)})^2$$
$$+ \frac{\tau_n}{2}\,(\Delta Q_n^{(k)} - (\Delta Q_n^c)^{(k-1)})^2 \tag{2.15}$$

where $\lambda_n^{min}$and λ_n^{max} denote the Lagrangian multipliers corresponding to the constraints on the n^{th} inverter control variable. τ_n is the proximal penalization factor associated with the proximal terms $(\Delta P_n^{(k)} - (\Delta P_n^c)^{(k-1)})^2$ and $(\Delta P_n^{(k)} - (\Delta P_n^c)^{(k-1)})^2$ on each subproblem. The subscript c refers to constant values. This parameter is used to ensure the convergence of the controlled voltage. The proposed approach enjoys fast convergence by adding proximal terms to the control variables P and Q deviation. The objective functions can be distributed to each PV inverter and coordinated locally and in parallel with other controllers. The equation of the proximal Jacobian version of the ADMM for local controllers in a multi-agent network can be derived in equation (2.17).

$$H_{nm}^{(k)} = \Delta P_n^{(k)} V_{nm}^{(P)} + \quad \Delta Q_n^{(k)} V_{nm}^{(Q)} \tag{2.16}$$

$$\mathcal{L}_n^{PJ-ADMM} = f_n^k + \Sigma(((\lambda_n^{max})^{(k-1)} - \left(\lambda_n^{min})^{(k-1)}\right) H_{nm}^{(k)}$$
$$+ \frac{\rho_n}{2} max\,(0, \left((V_n^M)^{(k-1)}\right) - V^{max})^2 + H_{nm}^{(k)}$$
$$+ \frac{\rho_n}{2} max\left(0, \left(-(V_n^M)^{(k-1)}\right) + V^{min})^2\right) - H_{nm}^{(k)}$$
$$+ \frac{\tau_n}{2}\,(\Delta P_n^{(k)} - (\Delta P_n^c)^{(k-1)})^2 + \frac{\tau_n}{2}\,(\Delta Q_n^{(k)} - (\Delta Q_n^c)^{(k-1)})^2)) \tag{2.17}$$

$$\tau_n > \rho_n \left(\frac{|N|}{2 - U_n} - 1 \right) \tag{2.18}$$

Algorithm 2.1. PJ-ADMM Adapted from (Deng, Lai, Peng & Yin, 2017)

Initialize the variables $\mathbf{\Delta P, \Delta Q, \lambda^{max}}$ **and** $\mathbf{\lambda^{min}}$

Set the voltage V at each node to 0.

Measure the voltage at the PCC

If the voltage is within the specified constraints $\mathrm{V^{min} \leq V^{M} \leq V^{max}}$

Then begin the local control iterations.

For k=0, 1… d

update the active power deviation ΔP and the reactive power deviation ΔQ in each subsystem by solving the optimization problem given by:

$\mathrm{argmin}_{\Delta p, \Delta q}\, \mathcal{L}_n^{\mathrm{PJ-ADMM}}$

Send the calculated values of ΔP and ΔQ to the control cycle of each inverter.

Constrain the values of ΔP and ΔQ by the following conditions:

$(-\mathrm{C_u})(\mathrm{P_n^{PV}})^{(\mathrm{k}-1)} \leq \Delta \mathrm{P_n^{(t)}} \leq 0$

$-(\Delta \mathrm{Q_n^{(max)}})^{(\mathrm{k})} \leq \Delta \mathrm{Q_n^{(k)}} \leq (\Delta \mathrm{Q_n^{(max)}})^{(\mathrm{k})}$

Update the variables λmax and λmin for each agent in parallel as follows:

$(\lambda_\mathrm{n}^{\mathrm{max}})^{(\mathrm{k})} = \max\,(0, (\lambda_\mathrm{n}^{\mathrm{max}})^{(\mathrm{k}-1)} + \rho_\mathrm{n}\, \mathrm{U_n}((\mathrm{V_n^M})^{(\mathrm{k})} - (\mathrm{V})^{(\mathrm{max})})$

$(\lambda_\mathrm{n}^{\mathrm{min}})^{(\mathrm{k})} = \max\,(0, (\lambda_\mathrm{n}^{\mathrm{min}})^{(\mathrm{k}-1)} - \rho_\mathrm{n}\, \mathrm{U_n}\, ((\mathrm{V_n^M})^{(\mathrm{k})} - (\mathrm{V})^{(\mathrm{min})})$

End

By applying the PJ-ADMM algorithm, the original optimization problem of the system can be partitioned into several subproblems. These subproblems are formed based on the constraints of the problem, and they are distributed among different agents. In a multi-agent control system, each agent is responsible for solving a specific subproblem that is part of the overall optimization problem. The subproblems are typically related to the control of a specific aspect of the system, such as voltage regulation in the case of the inverters mentioned in this paper. The agents optimize their local subproblems while sharing information with other agents to ensure the global solution is obtained. The subproblems are typically designed to be solved independently, with each agent having its own set of decision variables and local constraints. The solutions from each agent are then combined to form a solution for the overall optimization problem. This approach allows for a distributed and parallelized solution to the optimization problem, as each agent can work on its own subproblem without needing to communicate with every other agent. In the context of this paper, each agent in the multi-agent control system is a smart inverter. The inverters are equipped with voltage-support functions and are responsible for solving a specific subproblem related to the control of voltage within the system. The inverters work together to maintain the overall voltage within limits, and the solutions from each inverter are combined to form a solution for the overall optimization problem.

Once the voltage of any agent is outside the constraints, the model operator can return the values to the required range and minimize active power loss by optimizing the control variables. Furthermore, to improve the convergence speed of the voltage, proximal penalty factors and additional acceleration terms are used in the PJ-ADMM algorithm. This study used the acceleration factor $\mathrm{U_n}$ for fast updating in Lagrangian multipliers, which led to fast convergence. The condition for the parameter τ is given by equation (2.18), where τ depends on the number of inverters in the system, the acceleration factor, and the proximal penalization factor. For a set of inverters, a smaller τ provides faster convergence in the voltage control.

The details of the multi-block PJ-ADMM scheme are summarized in Algorithm 2.1. Here, $\mathrm{V^M}$ corresponds to the voltage measured at the PCC for a set of inverters after applying small changes in P and Q at each iteration. It should be noted that the voltage control scheme has an iterative manner. In each round k, the control system regulates the inverter's active and reactive powers and PCC voltage, followed by updating the Lagrangian multipliers. In this regard, at each iteration, all agents which are participated in control adjust the inverter outputs by monitoring the voltages measured at PCC as well as updating the Lagrangian multipliers λ_{max} and λ_{min}. The control cycle will continuously repeat with optimizing grid voltage support functions in parallel followed by updating the voltage at all nodes to be in the allowed ranges.

2.3 Verification

2.3.1 Case study

In this section, the performance of the proposed algorithm is validated using modified IEEE 13-bus distribution systems. The optimization problem is solved using YALMIP (Lofberg, 2004). Simulations of the 13-bus system are performed using MATLAB/Simulink 2021b and executed on a PC with an Intel i7-4790 3.60 GHz CPU and 16 GB RAM.

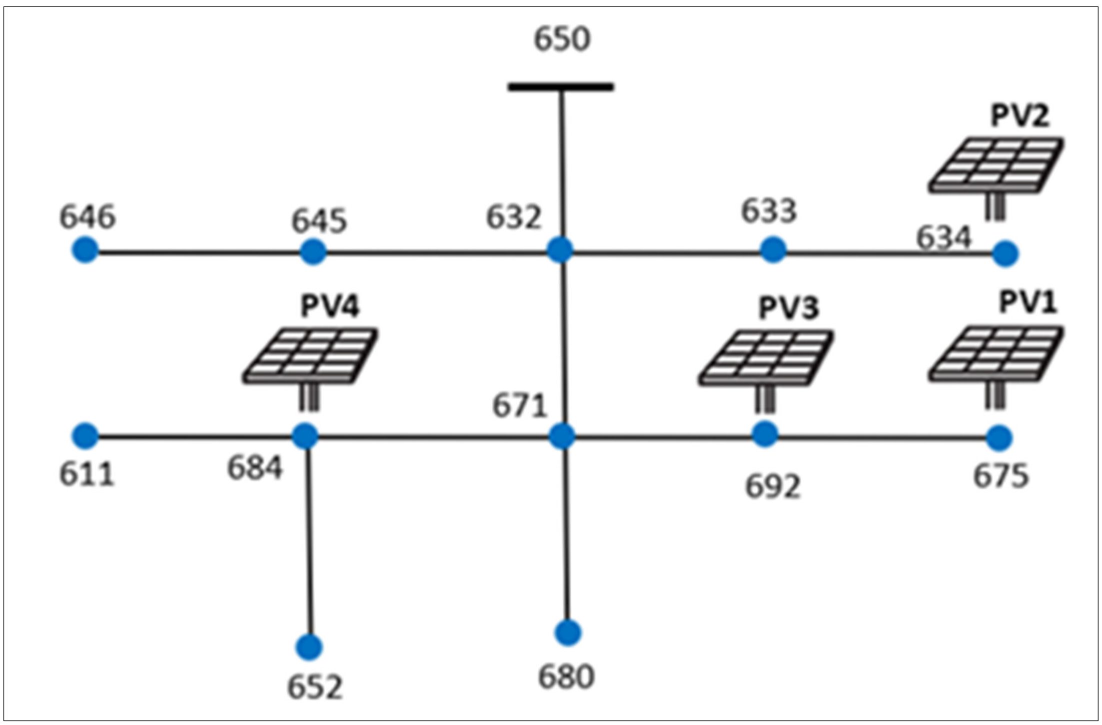

Figure 2.6 General Configuration of case study

The optimization algorithm used in this study takes network constraints into consideration. This study was conducted on pre-installed photovoltaic systems owned by customers. While it is technically possible for the algorithm to incorporate constraints such as generation efficiency and construction cost through pre-processing and simulation, this was not a focus of the current study, which instead focused on optimizing the utilization of already installed PV systems. The smart inverters used in this study are equipped with the PQ control mode as specified by the

IEEE-1547 standard. This mode allows for the control of both active and reactive power. In our study, we employed the PQ control mode and the optimization algorithm effectively communicated the necessary PQ signals between the photovoltaic system and the inverter, thus enabling the control of both active and reactive power.

The modified configuration of the IEEE 13-bus test feeder with the PV locations is illustrated in Figure 2.6. Four PV panels with similar solar irradiance profiles and commercial load profiles with a capacity of 200 kW were installed on buses 634,675,692 and 684. The detailed data of the loads and solar power profiles were adapted from (Tewari, Mohapatra, & Anand, 2020) which is shown in Figure 2.7. These data are modified based on the capability of the system used in this case study. Using the MAS-based topology, each inverter is an independent agent. All participating inverters are smart and operate with voltage-support functions. Each PV unit's active and reactive powers are regulated in each round of the optimization calculation cycle. In addition, uncertainties regarding the PV power and load disturbances are considered in the case studies. The system parameters are shown in p.u. The voltage constraint in each bus is set to [0.95, 1.05] p.u. Finally, the iteration number is considered to investigate the influence of related parameters on the convergence rate.

In this study, four possible scenarios are considered to indicate the effectiveness of the proposed control strategy. The performance of the implemented method at all smart inverters is analyzed when the system is experiencing under or upper voltage conditions, specifically at midday and an early night. An advantage of the proposed algorithm is that it improves the voltage profiles with a minimum amount of reactive power compensation and active power curtailment at each iteration. The performance of the proposed optimization method is compared with that of the base case without distributed control. The grid voltage support function does not need to be activated when the voltage falls below the limits.

Several parameters of the algorithm influenced the results. The term $\mathbf{C_u}$ is used to penalize active power curtailment. In this study, $\mathbf{C_u}$ is set to 1, which means that the inverters can curtail the maximum capacity of their active power when necessary. The active and reactive power penalization factors are $\mathbf{F_P}$= 1000 and $\mathbf{F_Q}$=500 (based on trial and error). Here, $\mathbf{F_P}$>$\mathbf{F_Q}$ for minimizing active power curtailment. The number of iterations is related to the penalty factor $\mathbf{F_P}$. Generally, small $\mathbf{F_P}$ yields a faster convergence. We also examined the effects of $\boldsymbol{\tau}$ on convergence speed.

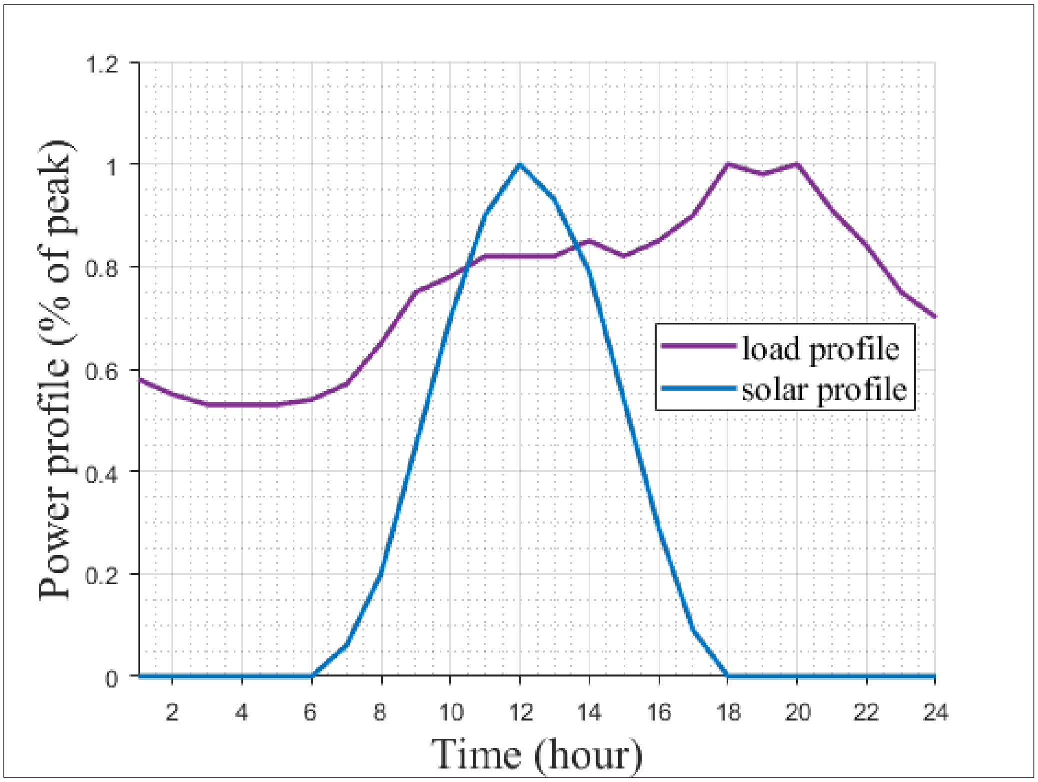

Figure 2.7 Load and PV profiles

2.3.2 Scenario I

Scenario I involve only active power control by curtailing the active power to reduce overvoltage when the PV output reaches its maximum value. Figure 2.8 (a)-(c) presents the 24 hours voltage profile of the network with the proposed controller under scenarios I and II compared with the profile without control. Figure 2.8 (a) shows the system's voltage profile before applying distributed control. The yellow line indicates the maximum boundary at Vmax = 1.05 p.u. It can be observed that the voltage rise problem occurs when there is low load demand and high PV generation.

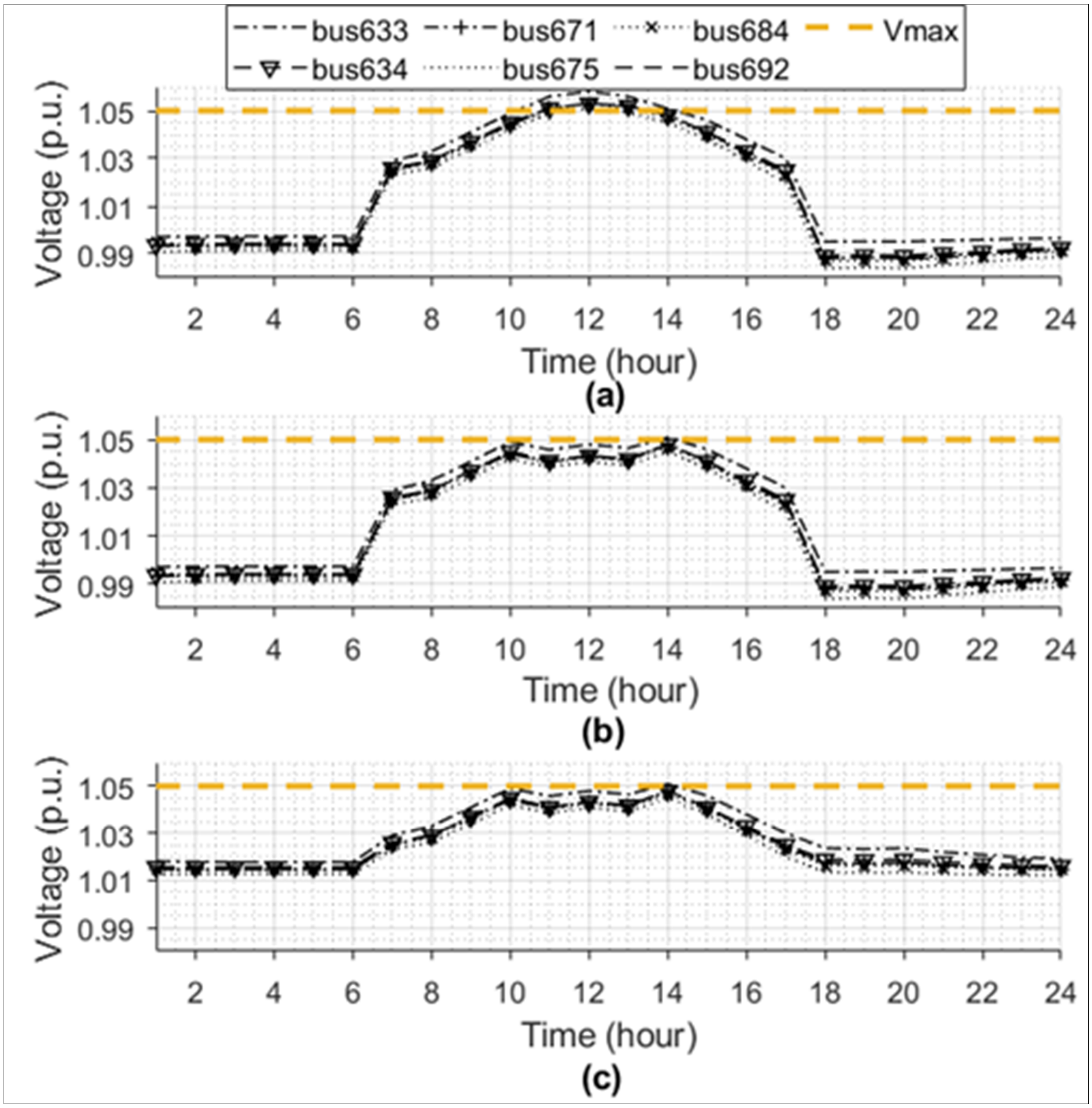

Figure 2.8 (a) 24h voltage profile of the system without control, (b) voltage profile with control under the scenario I, and (c) voltage profile with control under scenarios I and II

It can be observed that the voltage violates the upper limit on some buses in the time slots of 11:00-13:00. As shown in Figure 2.8 (a), the voltages on bus 634 exceeded the constraints, with a voltage of 1.053 at midday. The inverter at the end of the line at bud no 634 is selected to monitor the method's performance because it is more sensitive. In Figure 2.8 (b), we can see that using the developed PJ-ADMM algorithm, the voltage rise problem at noon is mitigated to 1.043 through an iterative control method.

Table 2.1 Results under scenario II

Time (h)	**Voltage without control (p.u.)**	**Voltage under scenario II (p.u.)**	**ΔQ (kVAr)**
20:00	0.983	1.013	20.208
21:00	0.985	1.012	20.215
22:00	0.986	1.012	20.226

2.3.3 Scenario II

The second scenario is the method of supporting voltage by reactive power in the under-voltage condition when the voltage of some nodes is lower than 1 p.u. during 1:00-16:00 and 18:00–24:00. In this scenario, there is no need to afford active power control. As shown in Figure 2.8 (c), when there is no PV generation and high load demand in the early evening, all buses experience low voltages. In this case, injecting reactive power can improve the voltage profile. In this scenario, we set the constraint for reactive power as the maximum capacity of the inverters. The results indicate that intelligent inverters can support the grid at night by injecting reactive power. It can be seen that the voltage drop occurs at 20:00, approximately 0.98 p.u., which is improved to 1.02 pm. Table 2.1 lists the total amount of reactive power provided to the inverters at bus 675 during 20:00–22:00 under scenario II.

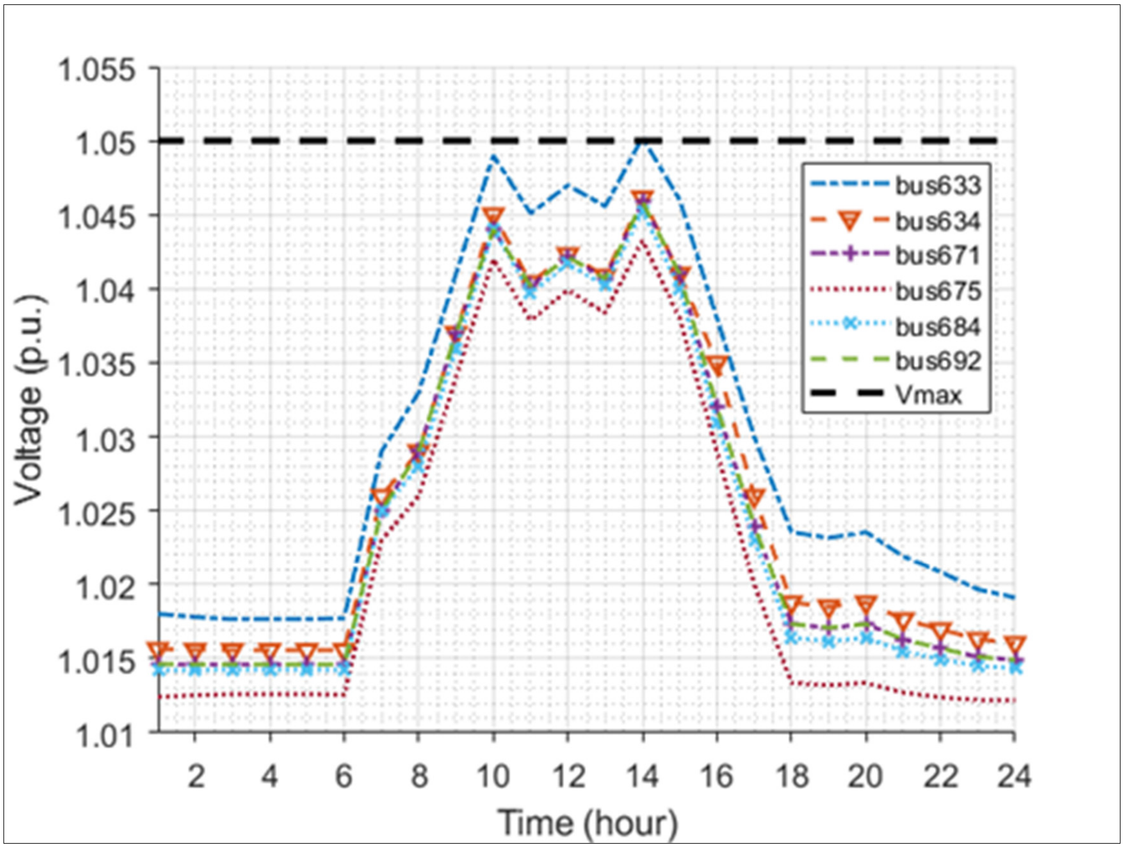

Figure 2.9 Voltage regulation under scenario III

2.3.4 Scenario III

Under scenario III, active power curtailment is disabled. Therefore, the PCC voltage is regulated using only reactive power when an overvoltage problem occurs. Figure 2.9 shows the optimized voltage profile under scenario III. It can be observed that the voltage rise during peak hours is controlled for all participating buses. Smart inverters start decreasing the overvoltage by absorbing a minimum amount of reactive power with no active power loss. In this case, smart inverters contribute to voltage control through a voltage support function by supplying or absorbing reactive power during voltage-rise conditions.

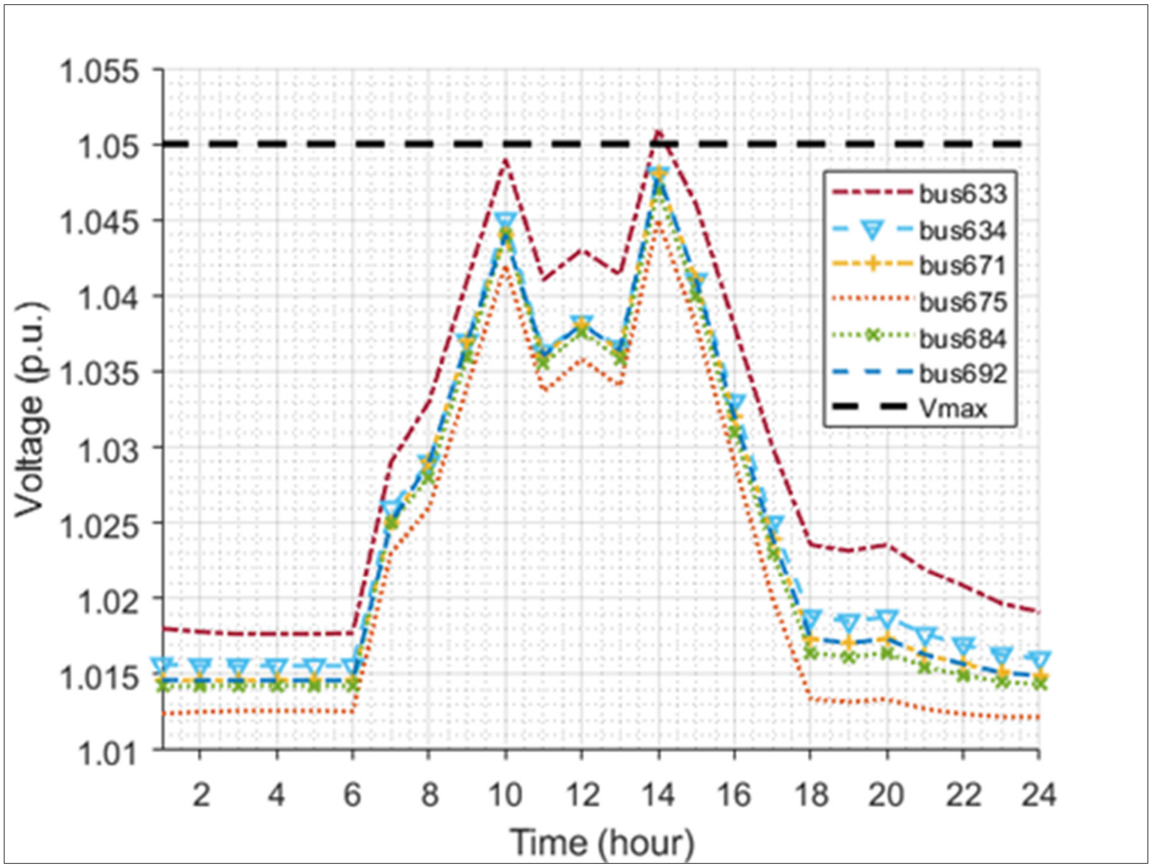

Figure 2.10 Voltage regulation under scenario IV

2.3.5 Scenario IV

The last scenario is designed to verify the effectiveness of intelligent inverters in voltage profile regulation with both active and reactive powers during periods of high solar power generation. In this case, smart inverters provide reactive power to the grid, along with the minimum curtailment of active power at each iteration, until the desired voltage limits are reached for all buses. Figure 2.10 shows the controlled voltage profiles under scenario IV. Table 3.2 illustrates the total active and reactive power curtailment under each scenario in the entire system during 11:00 -13:00 when PVs are at maximum output. In the last scenario, the total reactive power support at noon is approximately 33 kVAR. In contrast, the entire curtailed active power when the system experiences the maximum overvoltage is about 24 kW, which shows the impact of reactive power curtailment on the voltage profile of the system. Note that there was no voltage violation for the rest of the day; therefore, the voltage support functions were inactive during these hours. Table 2.2 presents the active and reactive powers received from the main network under the different scenarios at 12:00. These values reflect the amount of curtailed active and reactive powers, as shown in Table 2.3. Note that the PVs were at their maximum generation levels at midday.

Table 2.2 The total amount of curtailment in the system

Time (h)	**Scenario I**	**Scenario III**	**Scenario IV**	
	ΔP (kW	ΔQ (kVAr)	ΔP (kW)	ΔQ (kVAr)
11:00	27	52	23	31
12:00	32	48	24	33
13:00	24	51	26	32

Table 2.3. Active and reactive power in the swing bus at midday

Strategy	**P(kW)**	**Q(kVAr)**
Without control	1724	1060
Scenario I	1756	1060
Scenario III	1724	1109
Scenario III	1749	1094

Figure 2.11 shows the active and reactive power curtailment at bus-634. In this result, the performances of scenario III with only reactive power control and scenario IV with both active and reactive power curtailment are compared. Figure 2.12 shows the high-speed convergence of the voltage in bus-634 at midday under the different scenarios. Notably, the voltages are returned to the range of constraints by selecting the optimal value for the acceleration factor through the proposed algorithm for each agent independently in less than ten iterations while keeping the power curtailment at a minimum. In this case, better results were achieved when the curtailment acceleration factor was set to $\Upsilon_P = 10000$, the reactive acceleration factor was $\Upsilon_q = 100$, and the proximal penalization factor was set to $\tau = 0.0001$.

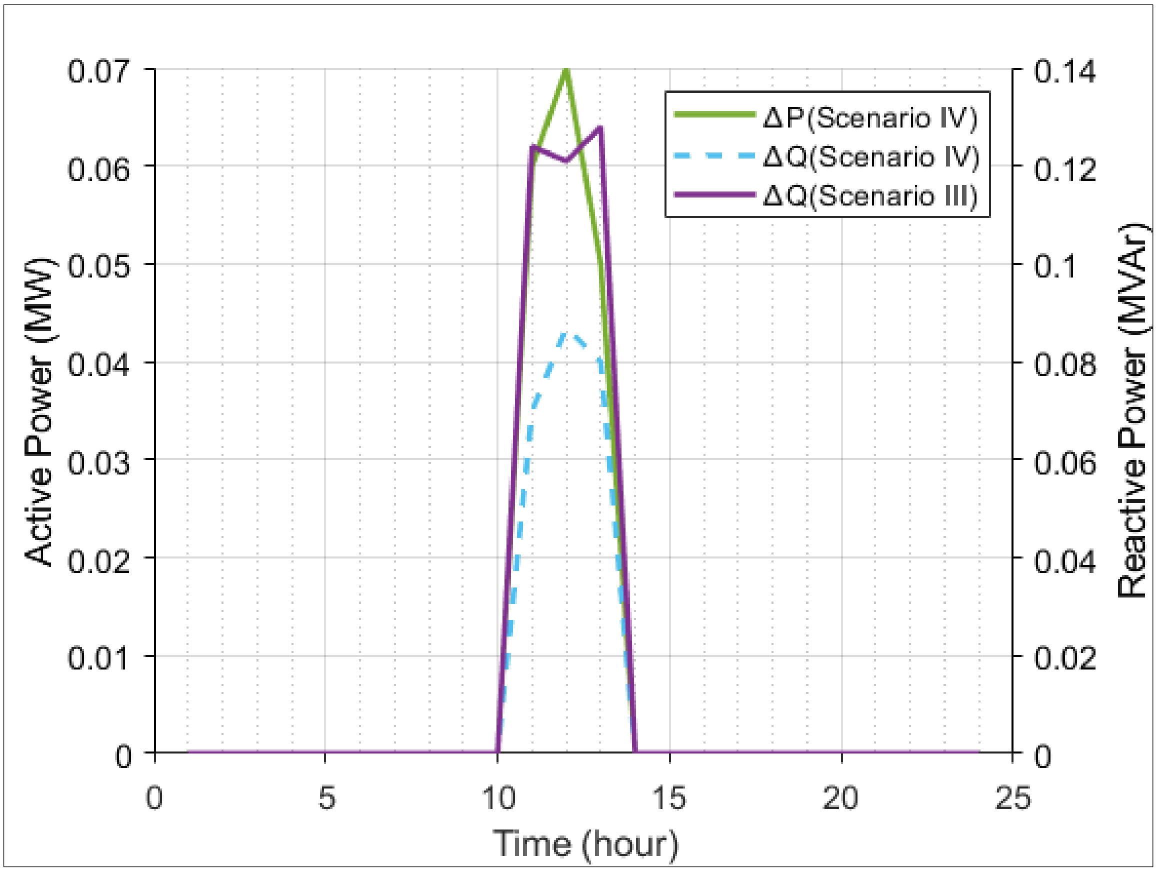

Figure 2.11 Active and reactive power curtailment at bus-634 under scenarios III and IV.

Mathematical equations of the PJ-ADMM algorithm demonstrate the feasibility of the proposed control scheme and its ability to control voltage through communication lines that allow agents to receive reference active and reactive power from the grid operator, which can be used to further optimize and coordinate their output to support the grid voltage. Based on simulation results, the proposed voltage control algorithm complies with the IEEE 1547 standard. In volt/VAR mode, the DER actively controls its reactive power output as a function of voltage. Intended to supply VAR only when needed, push local voltage back toward nominal. In volt/Watt mode, the DER actively limits the DER maximum active power as a function of the voltage. This mode can reduce the prevalence of very high voltages.

One potential connection between the use of PJ-ADMM for voltage control through active and reactive power and the IEEE 1547 standard is that both involve optimization of power flows in a distributed energy system. The IEEE 1547 standard sets requirements for the interconnection and operation of distributed energy resources, such as solar panels and energy storage systems, with the electric power grid. Voltage control through active and reactive power is a technique used to maintain stable voltage levels in the power grid. PJ-ADMM can be used to solve optimization problems related to both of these areas, such as determining the optimal power flows between distributed energy resources and the grid to meet the standard's requirements while also maintaining stable voltage levels. Additionally, PJ-ADMM can be used to solve optimization problems related to the IEEE 1547 standard by taking into account the constraints and requirements of the standard, such as the maximum and minimum power levels that distributed energy resources can produce and the maximum power that can be exported to the grid.

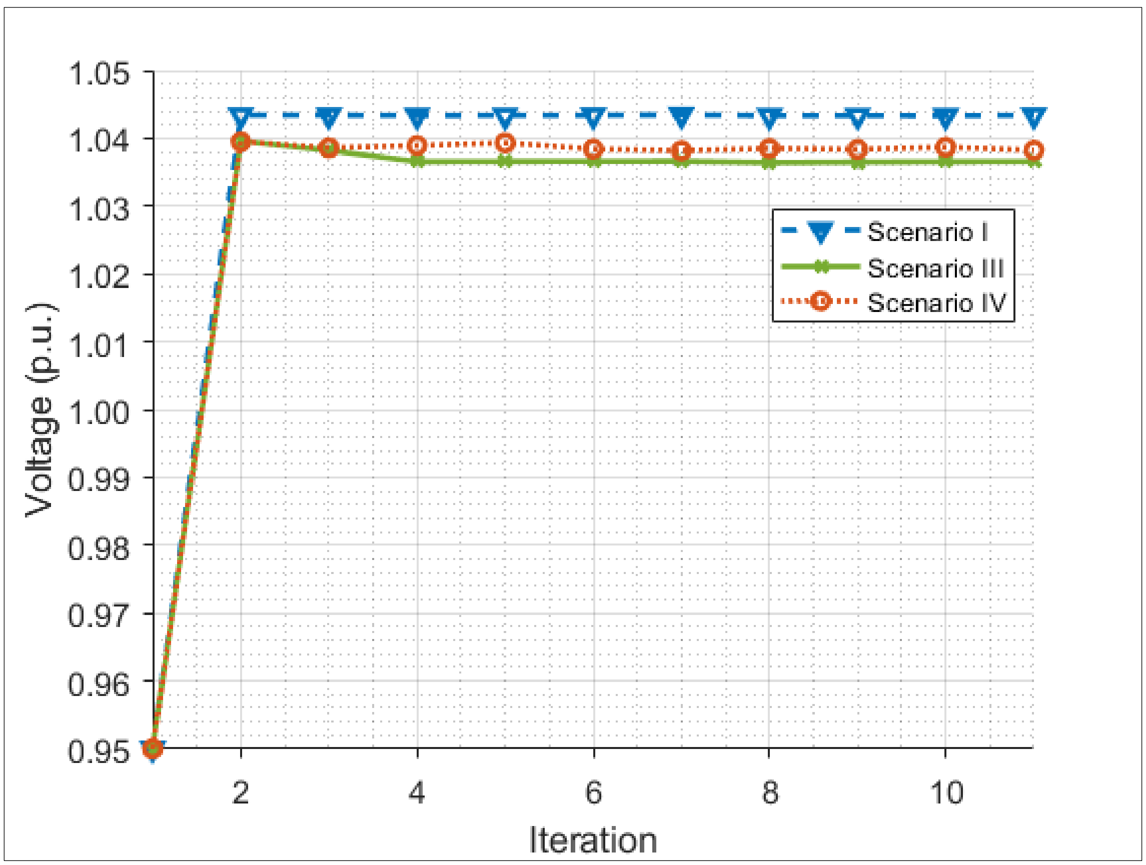

Figure 2.12 Voltage convergence at bus 634 at 12:00

Finally, a comparison of the results shows that applying the PJ-ADMM algorithm can improve the voltage profile of the multiagent system. It can be observed that the smart inverters at all buses start supporting the grid voltage locally and in parallel by injection/absorbing reactive power. Moreover, both control variables P and Q are updated with minimum curtailment at each iteration in parallel for all agents. Table 2.4 lists the voltages in bus 634 (with PV) and bus 633 (without PV) during peak hours. As can be seen, this method can maintain the voltage of all nodes in the allowed range, considering the uncertainties in the high penetration of solar PV networks. Smart inverters can also contribute to voltage control in connected buses without PV with reactive power control, which shows the ability of smart inverters in voltage regulation. The results demonstrated the flexibility and capability of the algorithm in smart inverters using reactive power, which considerably impacts voltage control. Scenario IV provides optimal regulation of the voltage profile with minimum curtailment compared with the other cases.

Table 2.4 Maximum voltage (p.u.) in buses 634 and 633 at midday

Bus	**Without control**	**Scenario I**	**Scenario III**	**Scenario IV**
634	1.053	1.043	1.036	1.038
633	1.058	1.047	1.041	1.043

2.4 CONCLUSION

In this paper, a modified Proximal Jacobian ADMM algorithm is presented for voltage regulation of A distribution network with a multi-agent structure. The optimization-based algorithm can mitigate the voltage violation by minimum changes in active and reactive power during abnormal conditions of voltage profiles. The distributed method shows the capability of smart inverters in handling the uncertainty associated with PVs and providing voltage support through reactive power with no active power loss during voltage rise periods. The simulation results validate the improvement in the performance of the system with high-speed convergence in a system with high penetration of photovoltaics

CHAPTER 3

DISTRIBUTED COORDINATED VOLTAGE CONTROL OF PV-BESS FOR POWER LOSS REDUCTION

In this chapter, we show how the optimal utilization of PV power can be achieved through a distributed coordinated voltage control system by controlling smart PV inverters locally using the PJ-ADMM algorithm in cooperation with the BESS. Coupling smart PV inverter features and BESS ensures voltage regulation within feasible bands with minimum active power loss. To this end, this chapter proposes a multi-objective control technique to support the grid voltage profile of a distribution power system. A robust control algorithm is implemented for solving the optimization problem. The control policies help assign storage capacity and estimate the minimum amount of power needed to be absorbed by storage from excess PV generation. Thus, the idea of storage sizing comes from a virtual curtailment strategy through the PJ-ADMM algorithm cycle by modifying the storage participation in voltage regulation, which gives rise to the efficient utilization of the BESS capability during power imbalance periods. Modified IEEE 33-bus and IEEE 141-bus networks are used for the case study in this chapter. Simulation results verify the control method's impact on the operation of the distribution system.

3.1 Introduction

The utilization of renewable energy is expected to see a significant boost in the coming years, with an anticipated increase of 50% in capacity from 2020 to 2024. This growth is further reflected in the projection of a 50% compound annual growth rate for the battery energy storage systems market during the same period. Solar PV technologies have experienced expanding growth over the last decade. It is expected that the global capacity in solar PV technologies will continue to raise to 9% yearly in the next 50 years (IRENA,2019). The shift towards using DERs is having an impact on how distribution networks are functioning. These networks were initially designed to function as passive networks, primarily consisting of loads. However, the increased integration of DERs is presenting technical difficulties in controlling the distribution networks. One of the major challenges is the issue of voltage rise caused by the power fed in from DERs. It is worth noticing that the voltage level in distribution networks is more affected by active power because of the high R/X ratio in the distribution systems compare to transmission systems (Shi& Sharma,2013).

Voltage regulation is a key power quality concern, to supply voltage within a secure limit. Nevertheless, the technical features of DERs, specifically PV inverters, offer potential solutions, such as active and reactive power control, to positively influence the grid voltage if utilized effectively. In order to realize this potential, new control algorithms must be developed to allow for coordination between DERs and their participation in voltage control through effective use of their active and reactive power control capabilities. Currently, inverters provide some optimal features such as active and reactive power control for improving the system voltage. Smart inverters can participate in voltage regulation by limiting the surplus active power through optimization control methods. However, active power curtailment affects PV owner revenue by limiting the solar PV power capacity.

The energy storage system is considered an efficient technology that can be used to solve grid voltage stability issues related to the high integration of PVs. The market of energy storage technology is estimated to experience significant growth around the world by 2050 (IEA, 2020b). Among different technologies in energy storage systems, battery energy storage systems (BESS) provide the highest applicability in distribution power systems. Energy storage devices have a finite amount of energy capacity, and their current cost is relatively high. Additionally, the distribution of electric energy customers is uneven and tends to be concentrated in certain locations at specific times. These factors make it necessary to conduct thorough research to determine the optimal location for battery energy storage systems, the best method for charging and discharging, and how to make the most of this technology.

The number of projects using BESS technology in smart power networks is rapidly increasing in recent years. In (Ayyagari, Gatsis, & Taha, 2017, November) optimal reactive power management is formulated for battery-photovoltaic inverters using distributed chance-constrained control technique. References (Von Appen, Stetz, Braun & Schmiegel, 2014). presented a PV-storage control system for voltage support using both active and reactive power control through limited communication infrastructure. A coordinated control scheme is developed (Zeraati, Golshan & Guerrero, 2016) for voltage control BESS using droop control. In (Wang, Bai, Yan & Saha, 2018), Real-time coordinated control of PV reactive power and BESS is proposed for voltage regulation of distribution systems with high PV penetration.

Using BESS in coordination with smart PV inverters is an efficient control technique for minimizing system losses and increasing capacities while keeping the grid voltage within acceptable limits. Voltage management of a distribution system considering the high uncertainty associated with solar PV still has room for development. In this regard, smart grids provide the development of active control technologies such as smart inverters for renewable energy sources and energy storage systems due to their economic benefits and sustainability. Different control methods have been proposed in the literature that allows PV-BESS to coordinate voltage control for demand management and peak shaving. Therefore, controlling active power using virtual storage systems has a lot of potential to achieve voltage control in distribution systems.

The main motivation for conducting this study is to address the challenges posed by the high penetration of PV resources in distribution networks, specifically the voltage violation issue due to the mismatch between loads and solar PV generation, and uncertainties associated with the intermittent nature of PV generation. In this work we focus on multi-agent distributed voltage control systems. The study aims to provide a robust and scalable control technique that can handle the high penetration of DERs in an extensive network using the proximal Jacobian ADMM (PJ-ADMM) algorithm for voltage control by optimizing the active and reactive power support in a large-scale network. This study ensured the optimal utilization of PV power by controlling smart PV inverters locally using the PJ-ADMM algorithm to distribute a centralized voltage control problem as it features a parallel updating process, rapid convergence, the capability to impose constraints, and superior global convergence performance. The application of additional penalty factors resulted in faster voltage convergence. However, curtailing the active power affects PV owner revenue by limiting the solar PV power capacity Hence, there is still a need of designing an optimization-based distributed voltage control based of PJ-ADMM algorithm that enjoy fast convergence rate and without power loss.

To achieve this goal, control algorithms must be developed for distributed coordinated voltage control based on iterative decomposition techniques. By joining the BESS to PV units, the voltage rise/drop problems can be controlled or eliminated according to objective functions through charging and discharging of the storage in peak PV generation and load consumption respectively. The distributed voltage control method provided by PV-BESS inverters can contribute to a better balancing of the power grid with minimum loss by increasing the local consumption during the low-load periods and serving the stored energy during high-load periods.

The utilization of coordinated control of PV and storage for voltage control in distribution networks has been presented in a number of recent studies (Zeraati, Golshan & Guerrero, 2017). However, most existing control methods did not consider the challenges of dealing with the high computational of optimization control algorithms in reasonable time for large and complex networks. The power loss in the PJ-ADMM algorithm motivates studying the implementation of virtual storage in the PJ-ADMM algorithm and how to charge/discharge to minimum BESS sizing can be allocated. This is made possible by utilizing energy storage systems to store excess energy generated by PVs during periods of low demand, which can then be released during peak demand hours.

This study builds on the technique presented in the previous chapter with extending the voltage control algorithm for power loss reduction in the distributed voltage control process. The control scheme provides both the power balance and the voltage regulation among the distributed energy resources and the overall power system. The distributed control policies assign storage capacity and estimate the minimum amount of power absorbed by storage, while taking into account technical limitations such as capacity and determines the charge/discharge power to be exchanged by buses. Thus, the idea of storage sizing comes from a virtual curtailment strategy through the PJ-ADMM algorithm cycle by modifying the storage participation in voltage regulation, which gives rise to the efficient utilization of the BESS capability during power imbalance periods

To the best of our knowledge, this research represents a novel endeavor in exploring the application of the PJ-ADMM algorithm for regulating voltage in high-penetration photovoltaic systems that are integrated into a large-scale network that features battery energy storage systems and operates in a completely decentralized manner, with a primary focus on reducing power losses. .The proposed method operates in two phases under different scenarios. In the first phase, the voltage control problem is formulated as a multi-objective optimization method. In the second phase, the BESSs are integrated with smart PV inverters to store excess solar power and control voltage. The control policies considered determine the active and reactive powers of the PV inverters and the charge/discharge power of the batteries.

This chapter focuses on a robust optimization-based voltage control technique through PV-battery coordination model of a distribution system dominated by PV systems. The model is developed aims to overcome the overvoltage and power loss challenges that arise with the high integration of PVs. The control scheme consists of a multi-agent control algorithm and the voltage control problem is defined as an optimization problem. In this technique, the agents coordinate with each other to estimate the required amount of curtailing active power and storage sizing needed to modulate the voltages rise.

3.2 Methodology

3.2.1 Proposed coordinated control strategy

In this section, an optimization technique is implemented to address the uncertainty associated with solar PV resources while managing the voltage of the distribution system using virtual BESS. The multi-objective control scheme is formulated and developed by a mathematical model using the developed PJ-ADMM algorithm. The main objective of the coordinated control scheme is to compute minimum solar active power and battery power control strategy to minimize voltage deviation, power losses, and solar power curtailment. The energy storage system participates in voltage management by absorbing or injecting active power. It is very important to keep the storage capacities within their considered power constraints.

3.2.2 PV uncertainty model

The active power consumption on the demand side and the solar PV power generation are the sources of uncertainty in the system which are considered in the control cycle. Several possible weather conditions are associated with active power production of PV and load demand at time step t. The variation in active power utilization and PV power production can be bounded as given in equations (3.1) and (3.2):

$$0 \leq \tilde{P}_{load}^{t} \leq \bar{P}_{load}^{t} \tag{3.1}$$

$$0 \leq \tilde{P}_{pv}^{t} \leq \bar{P}_{pv}^{t} \tag{3.2}$$

where $\bar{P}_{\mathrm{pv}}^{\mathrm{t}}$ and $\bar{P}_{\mathrm{load}}^{\mathrm{t}}$represent the uncertain values of the maximum PV power generation and load power consumption, respectively. $\bar{P}_{\mathrm{load}}^{\mathrm{t}}$ is formulated as the sum of the estimated load power demand and the deviation Δp from the forecasted amount at time step t (equation 3.3). $\bar{P}_{\mathrm{pv}}^{\mathrm{t}}$ is defined as the sum of the predicted PV power output and the deviation Δp from the forecasted amount at time step k (equation 3.4).

$$\bar{P}_{load}^{t} = P_{load}^{t} + \Delta P_{load}^{t} \tag{3.3}$$

$$\bar{P}_{pv}^{t} = P_{pv}^{t} + \Delta P_{pv}^{t} \tag{3.4}$$

3.2.3 Optimization-based voltage control

The optimization cycle will start with updating ΔP and ΔQ in each agent at time step k through the proximal Jacobian version of the ADMM for local controllers in a multi-agent network derived in equation (3.5). This equation is presented with details in the previous chapter. The optimization algorithm determines the PV inverters and storage buses as well as the amount of active power charging/discharging in the cycle of voltage regulation. The application of proximal terms helps solve subproblems with faster computation. In this regard, the objective problem will iteratively be solved using PJ-ADMM, where each participated inverter solves local optimization problems at each iteration.

$$\begin{aligned}\mathcal{L}_n^{PJ-ADMM} = {} & f_n^k + \Sigma(((\lambda_n^{max})^{(k-1)} - (\lambda_n^{min})^{(k-1)})(\Delta P_n^{(k)} V_{nm}^{(P)} + \Delta Q_n^{(k)} V_{nm}^{(Q)}) \\ & + \frac{\rho_n}{2} max\,(0, ((V_n^M)^{(k-1)}) - V^{max})^2 + (\Delta P_n^{(k)} V_{nm}^{(P)} \\ & + \Delta Q_n^{(k)} V_{nm}^{(Q)}) + \frac{\rho_n}{2} max(0, (-(V_n^M)^{(k-1)}) + V^{min})^2) \\ & - (\Delta P_n^{(k)} V_{nm}^{(P)} + \Delta Q_n^{(k)} V_{nm}^{(Q)}) + \frac{\tau_n}{2} (\Delta P_n^{(k)} - (\Delta P_n^c)^{(k-1)})^2\end{aligned} \tag{3.5}$$

The optimization problem has constraints imposed on it that set limits on the voltage profiles and deviations of the active and reactive power from the PV system (equations 3.6-3.8).

$$(-C_u)(P_n^{PV})^{(k-1)} \leq \Delta P_n^{(t)} \leq 0 \tag{3.6}$$

$$-\left(\Delta Q_n^{(max)}\right)^{(k)} \leq \Delta Q_n^{(k)} \leq \left(\Delta Q_n^{(max)}\right)^{(k)} \tag{3.7}$$

$$V^{min} \leq V^M \leq V^{max} \tag{3.8}$$

3.2.4 BESS sizing

BES can be classified as both a source or consumer of energy. In discharge mode, it serves as a generator with limited energy capacity, while in charge mode, it operates as a load for the network. The focus of the optimization method is to reduce active power loss, which is why network operators concentrate on the discharge mode. To comply with network constraints, providing energy at optimal rate is of great significance. The aim is to allocate BES for maximum benefits from discharge mode. The BES model includes active and reactive power operating with no control over voltage and the rating of BES is assumed to be constant. By the end of Phase I of this study, the minimum required power curtailment, denoted by ΔP, for voltage-rise mitigation is computed using the PJ-ADMM algorithm. The control cycle considered in this methodology is included active power curtailment from PV inverters and charge/discharge power from virtual storages in the control cycle of the algorithm. This method will contribute to keeping the power grid balanced by smoothing out the demand peaks through the algorithm coupling the BESS with PV inverters and improving the local consumption during the low-demand periods in the distribution system.

Phase II presents the application of the PJ-ADMM algorithm for power loss reduction using the BESS, where the curtailed powers are specified for the charging or discharging operations of the BESS to regulate the voltage profiles. Therefore, BESSs are considered active power generators or consumers in the network. The BESS sizing problem has been formulated as a mathematical programming method using the PJ-ADMM algorithm at high PV energy penetrations. In the presence of uncertainties, once a voltage violation is detected in any node, the optimization control algorithm will be active in computing the minimum amount of active power curtailment required to mitigate the voltage rise. Therefore, the charging power of the BESS at each hour of running the optimization algorithm is the same as the curtailed active power of the PVs. When the load demand exceeds the generated PV power, the BESS starts to discharge. In this way, the active power of PV inverters will be cut by saving of the excess active power in the storage which helps alleviate the voltage rise issue in high PV generation periods. In peak load periods, the stored energy in BESS will be used for improving the voltage profile of the grid during voltage drop periods.

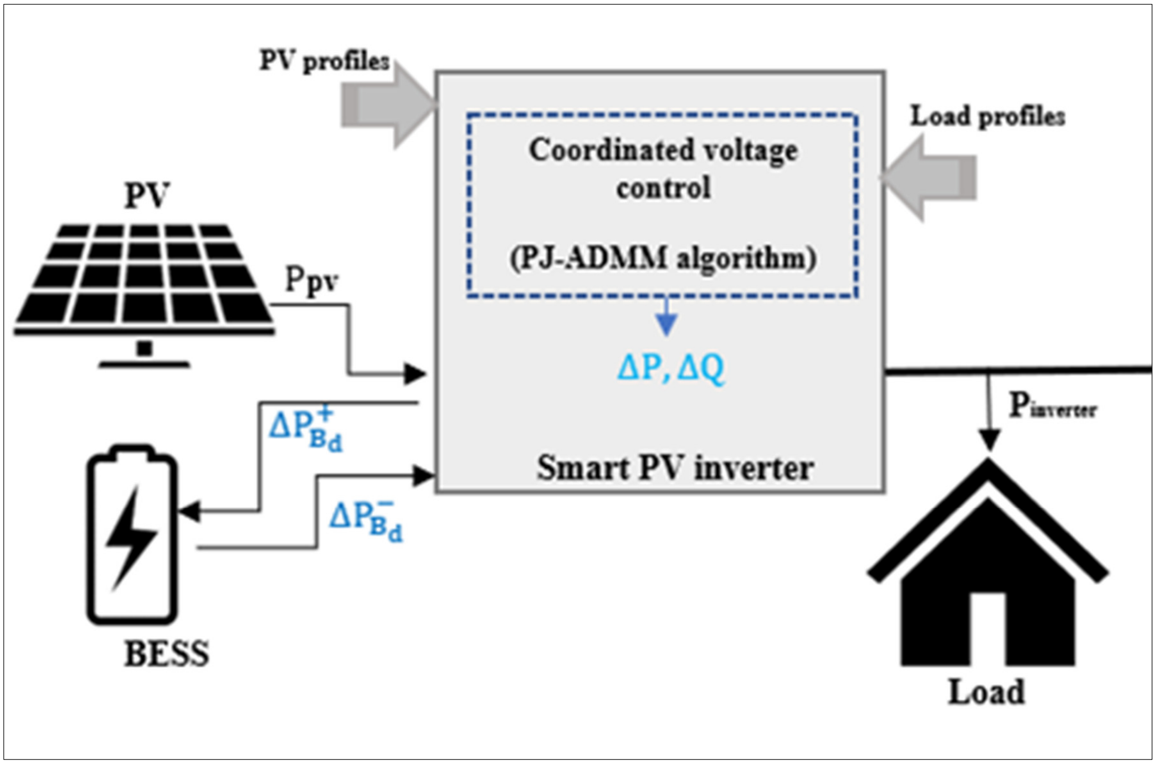

Figure 3.1 General outline of the proposed coordinated control system

The general structure of the proposed optimization method is shown in Figure 3.1. The JP-ADMM algorithm is applied to the control loop of the PV inverter through the grid voltage support function. The distributed optimization algorithm iterates over an order and the proximal penalization functions which are updated in parallel till the convergence is preserved. The coordinated voltage control policy determines storage integration into the voltage profile. In this phase, the reactive power of the BESS is not considered in the optimization cycle. The participation of storage systems is proportional to their capacity, based on the load demand at each hour of the day. The results show how the developed mathematical optimization algorithm allocates BESS capacity to voltage control. Algorithm 3.1 presents the PJ-ADMM algorithm and virtual BESS.

Algorithm 3.1: PJ-ADMM algorithm and virtual BESS

1 Phase I:
2 Initialize the variables ΔP, ΔQ, λmax, and λmin. Set the voltage V at each node to 0.
3 Measure the voltage at the Point of Common Coupling (PCC).
4 If the voltage is within the specified constraints, $V^{min} \leq V^{M} \leq V^{max}$, then begin the local control iterations.
5 For k = 0, 1, ..., d, update the active power deviation ΔP and the reactive power deviation ΔQ in each subsystem by solving the optimization problem given by:
6 $\mathrm{argmin}_{\Delta p, \Delta q} \mathcal{L}_n^{PJ-ADMM}$
7 Send the calculated values of ΔP and ΔQ to the control cycle of each inverter.
8 Constrain the values of ΔP and ΔQ by the following conditions:
9 $(-C_u)(P_n^{PV})^{(k-1)} \leq \Delta P_n^{(t)} \leq 0$
10 $-(\Delta Q_n^{(max)})^{(k)} \leq \Delta Q_n^{(k)} \leq (\Delta Q_n^{(max)})^{(k)}$
11 Update the variables λmax and λmin for each agent in parallel as follows:
12 $(\lambda_n^{max})^{(k)} = \max(0, (\lambda_n^{max})^{(k-1)} + \rho_n U_n((V_n^M)^{(k)} - (V)^{(max)})$
13 $(\lambda_n^{min})^{(k)} = \max(0, (\lambda_n^{min})^{(k-1)} - \rho_n U_n((V_n^M)^{(k)} - (V)^{(min)})$
14 End
15 Phase II:
16 For each hour h = 0, 1, ..., 24, repeat the following steps:
17 For each BESS, Bn = 0, 1, ..., 4, absorb or inject ΔP to/from the BESS.
18 For all BESS, update equations (9) and (10) to determine the charging/discharging active power.
19 Update the charging power $P_{B_d,h}^{charge}$ and discharging power $P_{B_d,h}^{Discharge}$ in the optimization cycle.
20 Measure the voltage at the PCC.
21 If the voltage is within the specified constraints, $V^{min} \leq V^{M} \leq V^{max}$, then end the iteration.
22 Determine the required BESS capacity and charging/discharging rates.

3.2.5 BESS operation constraints:

The BESS is also subject to charging power ($\mathrm{P}^{\mathrm{t}}_{\mathrm{charge}}$) or discharging power ($\mathrm{P}^{\mathrm{t}}_{\mathrm{discharge}}$) constraints. The stored power of the battery system at any time step t should not surpass the considered limits. The boundary on the power charging and discharging can be represented as (equations 3.9-3.11), where $\mathrm{P}_{\mathrm{max}}$ is the maximum charge/discharge power.

$$0 \leq P^{t}_{charge} \leq P_{max} \tag{3.9}$$

$$0 \leq P^{t}_{discharge} \leq P_{max} \tag{3.19}$$

$$\mathrm{P}^{\mathrm{t}}_{\mathrm{charge}} . \mathrm{P}^{\mathrm{t}}_{\mathrm{discharge}} = 0 \tag{3.11}$$

Constraints (3.9) and (3.11) enforces that the power output of the BESS cannot surpass its power capacity. Constraints (3.12) enforce that the energy stored in the batteries should be maintained within an acceptable range to avoid excessive charging/discharging and increase the battery's longevity.

$$E_{min,Battery} \leq E_{Battery}(t) \leq E_{max,Battery} \tag{3.12}$$

In the given context, T represent the overall number of time intervals over the control horizon and $\Delta \mathrm{t}$ is the time step duration, respectively. $\mathrm{E}_{\mathrm{Battery}}(\mathrm{t})$ signifies the energy level of at time t. $\mathrm{E}_{\mathrm{max,Battery}}$ and $\mathrm{E}_{\mathrm{min,Battery}}$denote the upper and lower bounds of its energy capacity, respectively. The amount of energy stored in a BESS can be calculated by using the following equation (3.13):

$$E_{Bat}(t+1) = E_{Bat}(t) + P_{Bat}(t)\,\Delta t$$

$$E_{Bat}(t+1) = E_{Bat}(t-1) + P_{Bat}(t-1)\Delta t + \Delta P_{Bat}(t)\Delta t$$

$$E_{Bat}(t+1) = E_{Bat}(t-2) + P_{Bat}(t-2)\Delta t + P_{Bat}(t-1)\Delta t + \Delta P_{Bat}(t)\Delta t$$

$$\dots$$

$$E_{Bati}(t+1) = E_{Bati}(1) + P_{Bati}(1)\Delta t + P_{Bati}(2)\Delta t + \dots + \Delta P_{Bat}(t)\Delta t \tag{3.13}$$

The initial energy of each battery, represented by $E_{Bat}(1)$, can be expressed using following equation (3.14) as follows:

$$E_{Bat}(t+1) = E_{Bat}(t) + (P_{charge}(t)\eta_{ch} - P_{discharge}(t)/\eta_{dch})\,\Delta t \tag{3.14}$$

Note that there are some losses in the batteries owing to the internal resistance, which is given by the charging and discharging efficiency of the batteries with η_{ch} and η_{dch}. These values can vary depending on the case study, and have been approximated in different ways. they can be a single constant value, or as functions of the charging/discharging rate of BESSs. However, a linear relationship exists between the charging efficiency and the charging rate as given in (3.15). The BES can be described using constant coefficients α and β. The same approach can be applied to the discharging mode (Amoroso & Cappuccino, 2012).

$$\eta_{ch} = \alpha_n - \beta_n P_{charge} \tag{3.15}$$

In the case if this study, the equations (3.16) and (3.17) are shown the active power charging and discharging of the battery n^{th} at bus d, where $B_{n,d,h}$ is the set of BESS installed in the system for 24 hours each time step h.

$$P_{B_{n,d,h}}^{charge} = \eta_{ch} \times \Delta P_{B_{n,d}}^{+} \tag{3.16}$$

$$P_{B_{n,d,h}}^{Discharge} = \Delta P_{B_{n,d}}^{-}/\eta_{dch} \tag{3.17}$$

Here, $P_{B_{d,h}}^{charge}$ and $P_{B_{d,h}}^{Discharge}$ are the power stored and injected by each storage, respectively, and the charging and discharging of active power at the n^{th} BESS at bus d is equal to $\Delta P_{B_{n,d}}^{+}$ and $\Delta P_{B_{n,d}}^{-}$ respectively. The energy stored in each BESS is selected to equal its capacity, considering the efficiency of 95%. $\Delta P_{B_{n,d}}^{+}$ and $\Delta P_{B_{n,d}}^{-}$ are assumed to be the active power deviations. Their sign is considered to be either positive or negative, depending on the BESS operating mode. When the battery operates in the charging mode, ΔP is positive. When the battery works in the discharging mode, ΔP is negative. The algorithm determines which BESs from the network are chosen to participate in control cycle and how much power are charged or discharged to satisfy the voltage control constraints over the whole network. The algorithm determines which BESs from the network are chosen to participate in control cycle and how much power are charged or discharged to satisfy the voltage control constraints over the whole network.

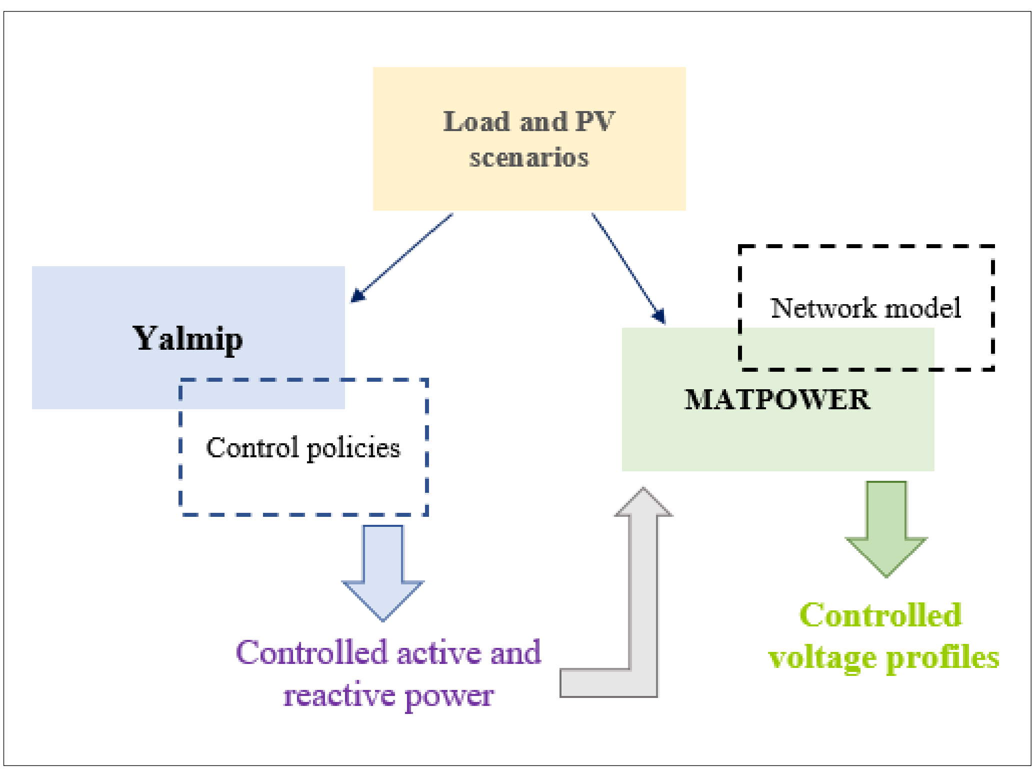

Figure 3.2 Overview of an interface between MATPOWER and YALMIP

3.3 Validation

3.3.1 Case studies

The performance and scalability of the proposed control strategy for the modified IEEE 33-bus and 141-bus test systems were validated through a comprehensive case study. The study utilized various software tools to assess the efficacy of the proposed model. Figure 3.2 presents the different software tools used in the validation process. The power flow analysis and computation of voltage profiles were performed using the MATPOWER package 7.0 (Zimmerman & Murillo-Sanchez, 2019). The optimization problem was solved utilizing the YALMIP toolbox.

The control cycle of the algorithm started with the measurement of the voltage at the point of common coupling (PCC) and a check for voltage constraints. Subsequently, the active and reactive power deviations were updated in each subsystem. The load and PV scenarios of the control buses were then sent to the control cycle of each smart PV inverter, where the values of ΔP and ΔQ were calculated at each iteration. The minimum required amount of active power curtailment was then sent to the control policies, which determined the charge/discharge power of the storage system during peak hours. Finally, the MATPOWER package was used to analyze the power flow and compute the overall voltage profiles of the system.

3.3.2 IEEE 33-bus test system

The proposed control strategy for the IEEE 33-Bus test system is depicted in Figure 3.3. This study involved the integration of 20 PV systems, each having an equivalent capacity of 0.2 MW, into the grid. The system was equipped with four distributed BESSs with a capacity of 2.5 MWh each. The voltage constraints for each bus in the system were set to [0.98 1.05] per unit (p.u.). The increasing integration of PVs into the grid results in voltage fluctuations and variations, making it crucial to develop intelligent and optimal control strategies to maintain the voltage within the specified constraints. In this study, two case studies were conducted to evaluate the performance of the proposed algorithm. The ratio of the peak-hour PV generation to the load is presented in Table 3.1. The data for the loads and solar power profiles were obtained from (Tewari, Mohapatra, & Anand, 2020), with a 10% increase in all loads to stress the network. It is important to note that high PV power generation exacerbates the control problem, highlighting the need for effective control strategies. The proposed algorithm aims to address these challenges by offering a comprehensive solution for the optimal control of the system.

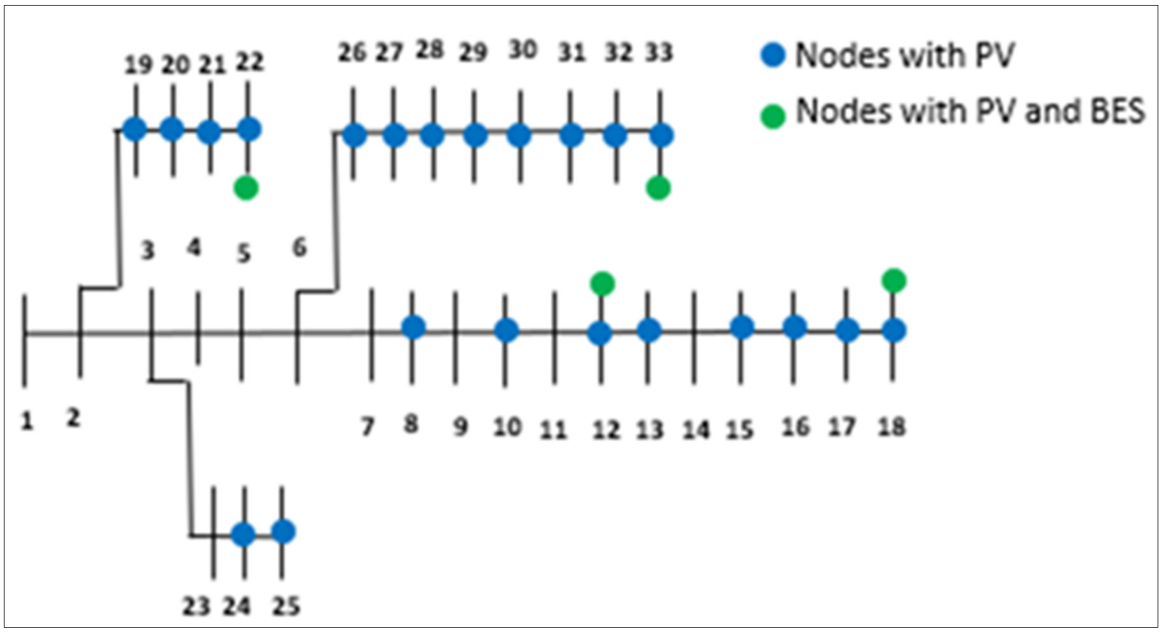

Figure 3.3 Configuration of case study on 33-bus system

Table 3.1 The ratio of PV generation compares to the load.

Time(h)	**PV/Load %**
11:00	28%
12:00	31%
13:00	25%

The present section delves into the results of the optimal sizing of the BESS. The optimization problem is designed with a prime focus on minimizing PV power curtailment during peak generation, energy losses, and voltage deviation. To achieve this goal, the PJ-ADMM algorithm determines the minimum power to be shared between batteries and the grid, proportional to the storage capacities. The active power control's influence on the voltage profile is studied, with the assumption that reactive power has zero impact. This method implements a coordinated optimization problem for smart inverters under the uncertainty introduced by the variations in power sources and loads. The BESS can limit the generation of power from PV inverters by absorbing excess active power, and the charging mode can be considered a network load. The energy stored in the storage systems can serve as backup power during the discharging mode when the BESS provides energy to the network. The excess power will be calculated through the PJ-ADMM algorithm and shared proportionally between storage systems according to their capacities.

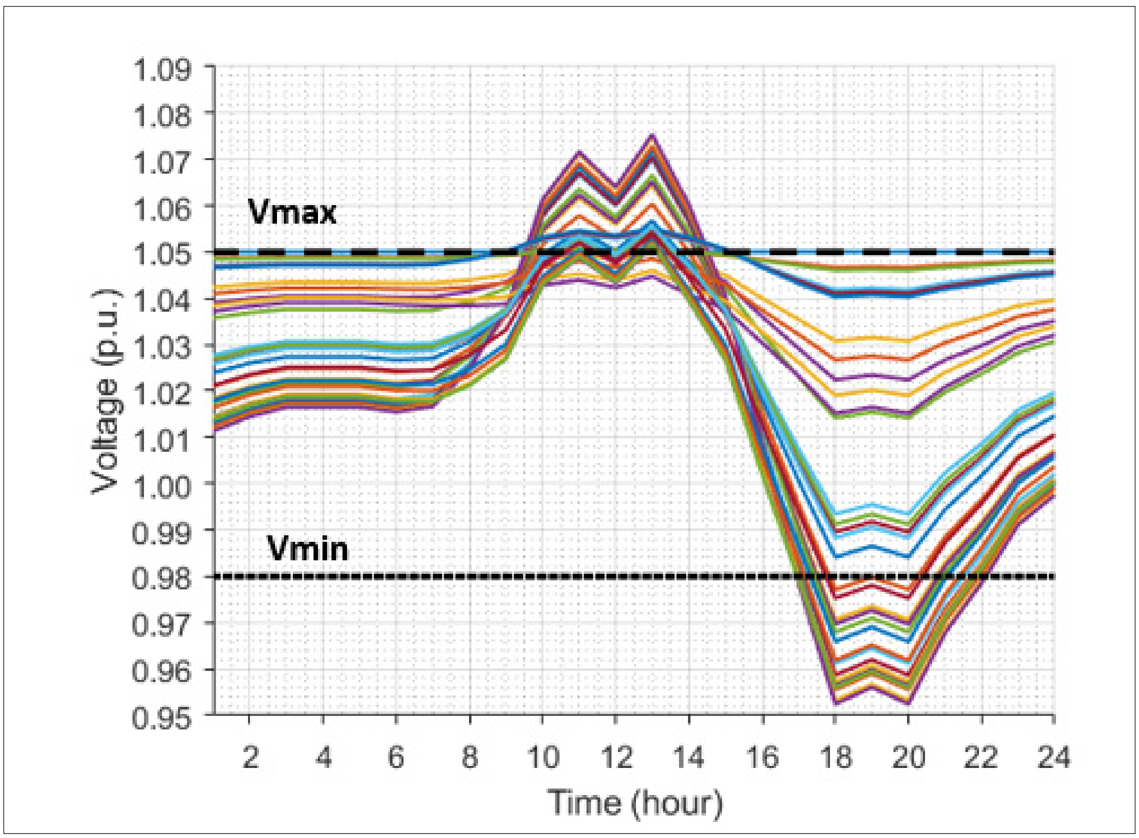

Figure 3.4 Voltage profiles of 33-bus system with no voltage control

To showcase the impact of high integration of PVs on the grid's output voltage, a power flow was performed in the base case without control. Figure 3.4 shows the voltage profile of the network in the absence of control, and it can be observed that the voltages violate the constraints at noon on all buses connected to PV systems. The impact of PV power variation on grid voltage violation can be seen in the voltage profile between 10:00-15:00, with voltage rising up to 1.075 p.u. during peak generation times. Figure 4.5 shows the 24-hour voltage profiles after applying the coordinated control policies using the PJ-ADMM algorithm, and the results demonstrate that the voltage is maintained within the defined ranges after the control actions are applied. The algorithm is integrated into the control loop of the PV inverter through the grid voltage support function. Excess active power injection from PV inverters is absorbed by the BESS to mitigate the voltage rise problem during 10:00-15:00. All storages should participate in the voltage control cycle in a fair manner, proportional to their capacity. The proposed technique significantly improves voltage, validating the scalability and robustness of the method, as shown in the results.

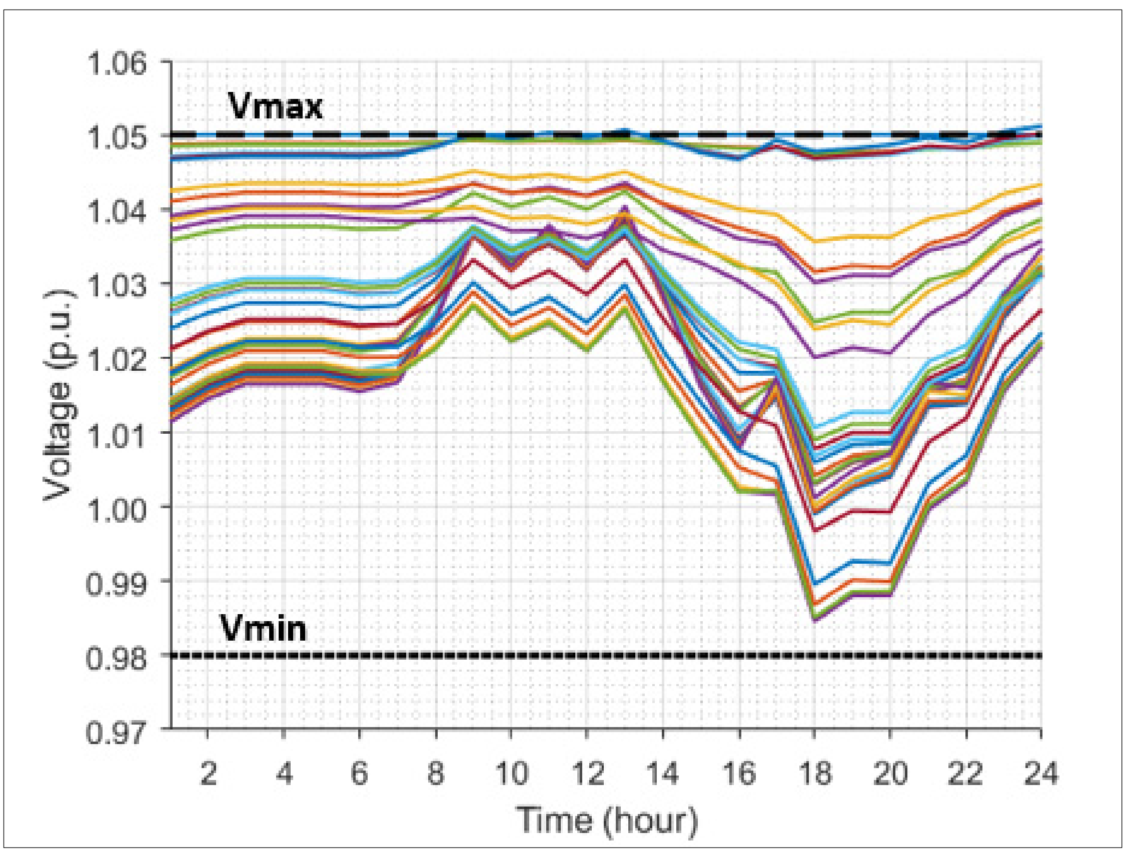

Figure 3.5 The 24h voltage profile of 33-bus network with PV-BES voltage control

The allocation of the BESS maximizes the benefits of the discharging mode, providing peak shaving and load control in the system. The results in Figure 3.5 indicate that the control scheme can handle the voltage problem by curtailing a small amount of energy and storing it in virtual batteries instead of wasting it. The total charge and discharge rates for each hour of the day for four BESSs are shown in Figure 3.6. The BESSs are charged when PVs generate a high amount of energy and are discharged during peak load periods, especially during 17:00-22:00. The power is proportionally shared between the BESSs according to their capacity and load demand in the optimization algorithm cycle. The results illustrate that the BESSs are charged during high PV generation and discharged during high load demand periods. The charge and discharge efficiencies were set to 95%. During the peak hour of the day at 13:00, approximately 1.8 MW of active power losses were reduced by charging four BESSs, which is almost the same as the maximum discharging rate at 20:00. The results validate the effectiveness of the proposed mathematical optimization method under peak-shaving or load-leveling scenarios.

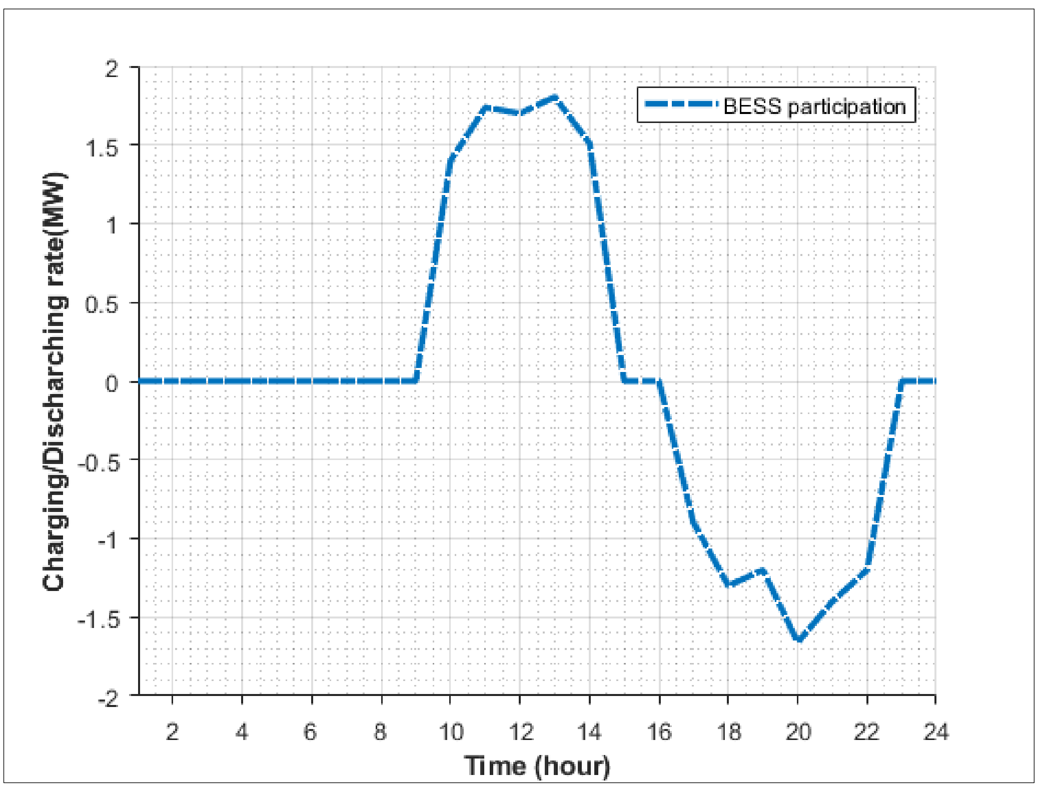

Figure 3.6 BESS participation in 33-bus system

3.3.3 IEEE 141-bus test system

The proposed voltage control model has been thoroughly tested on both small-scale and large-scale systems, showcasing its versatility and scalability. In the case study, the system was expanded from a 33-bus network (comprised of 20 PV smart inverters and 4 BESSs) to a 141-bus network (comprised of 35 PV smart inverters and 3 BESSs), and the capacity of the PV panels was increased from 0.2 MW to 0.7 MW. The results from the case study on the 141-bus system, which was conducted using the same PV generation and load data as previous case studies, highlight the scalability of the proposed method. It was ensured that each bus maintained a secure voltage within the range of [0.95, 1.05] per unit and that the PV panels were capable of operating at a power factor of up to 0.9.

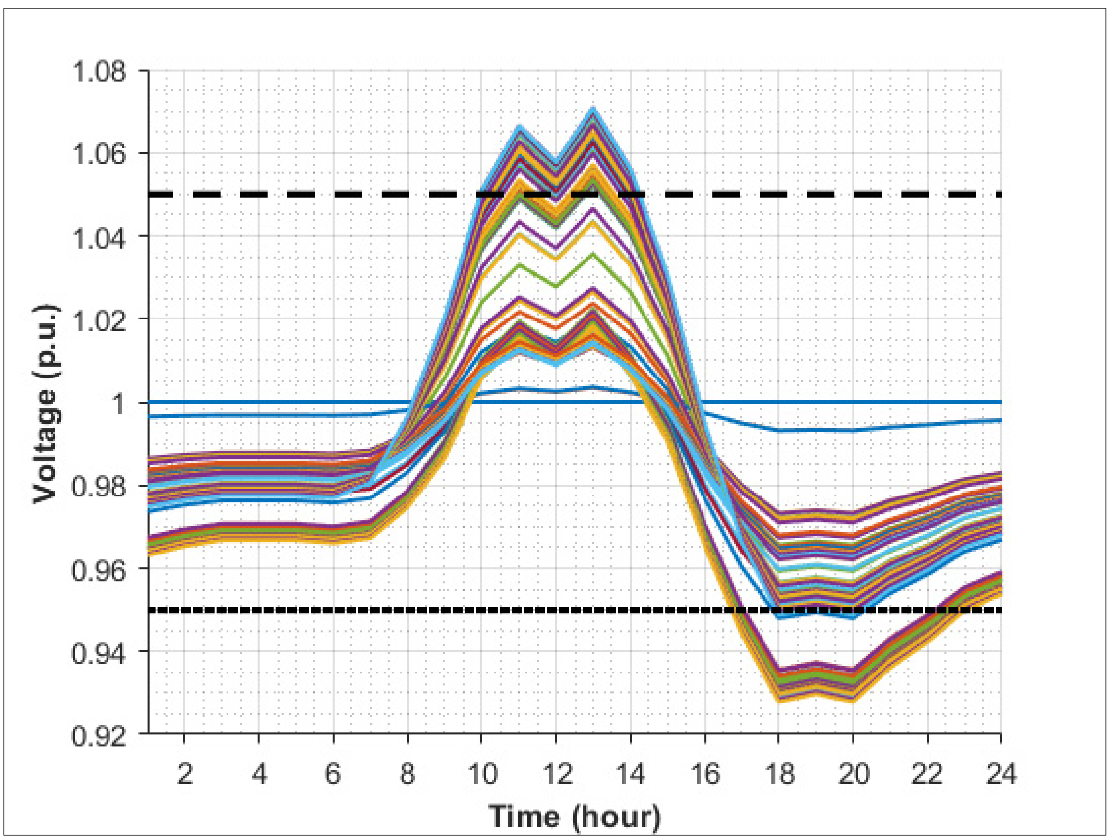

Figure 3.7 Voltage profiles of 141-bus system with no voltage control

As shown in Figure 3.7, without the proposed distributed voltage control strategy, the voltage profiles of the 141-bus system exceeded the maximum voltage limit between 10:00 and 14:00. Over-voltage (1.07 p.u.) was observed at midday, while some buses experienced under-voltage (0.92 p.u.) during the evening. With the suggested voltage control scheme, the system operator can effectively address the issue of rising voltage through voltage regulation process. As illustrated in Figure 3.8, after applying the coordinated voltage control policy using the PJ-ADMM algorithm, a significant improvement in the voltage profile was achieved, demonstrating the scalability of the proposed method.

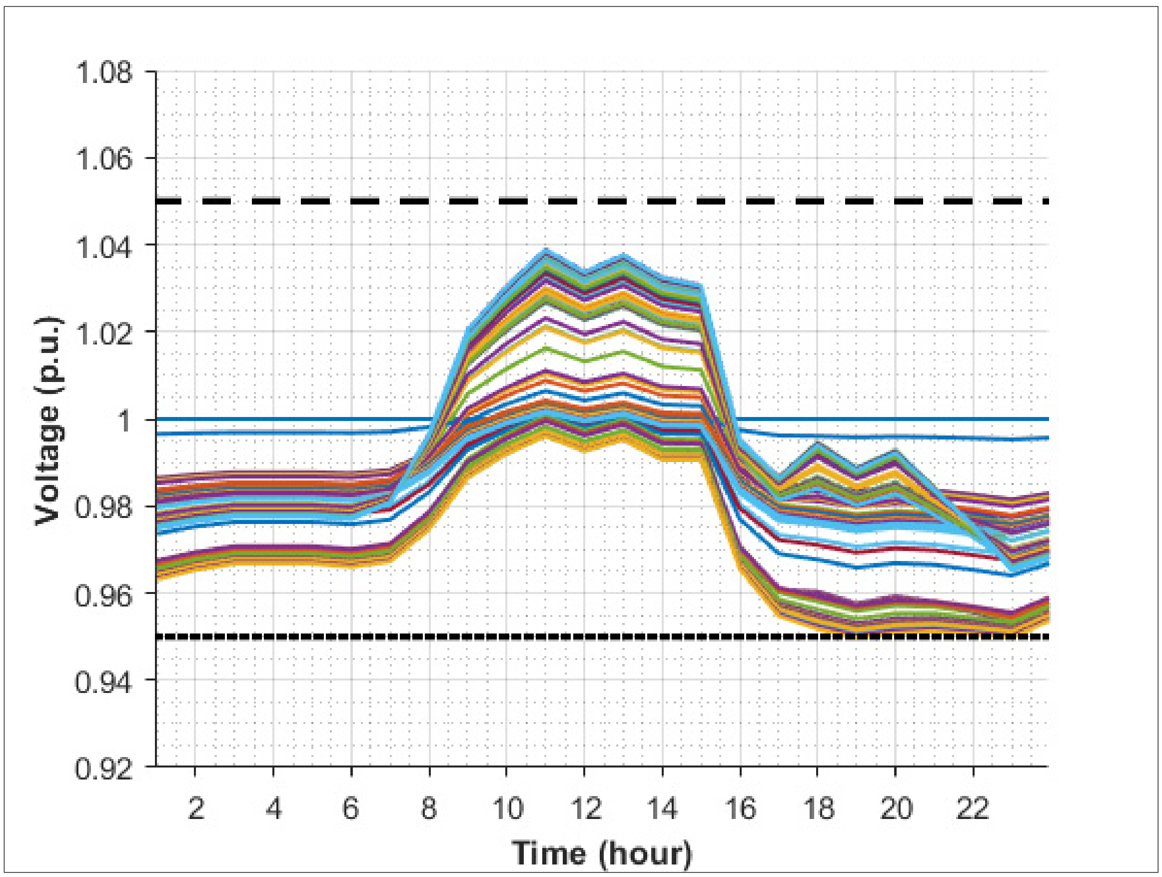

Figure 3.8 The 24h voltage profile of 141-bus network with PV-BES voltage control

The figure shows 24-hour profiles of bus voltages in the 141-bus system and it can be seen that when voltages increase more than 1.05 pu, the BESS will start to charge and absorb the active power from the grid. The results of the case studies demonstrate that the proposed method is both robust and scalable, making it a viable solution for voltage control in large-scale photovoltaic-integrated power systems. The BESS start to discharge power to the grid when voltages drop below 0.95 pu. When all bus voltage levels are stabilized within normal limits, there is no longer a need to make changes to the active power output of the BESSs.

This study aimed to examine the potential reduction in power loss in power systems with high PV penetration and to highlight the role of storage systems in mitigating these losses. To that end, we calculated the maximum reduction in power loss at midday and found that the use of virtual battery energy storage systems (BESS) with the PJ-ADMM algorithm resulted in a reduction of approximately 2.5MW per BESS, or up to 10 MWh in daily energy losses.

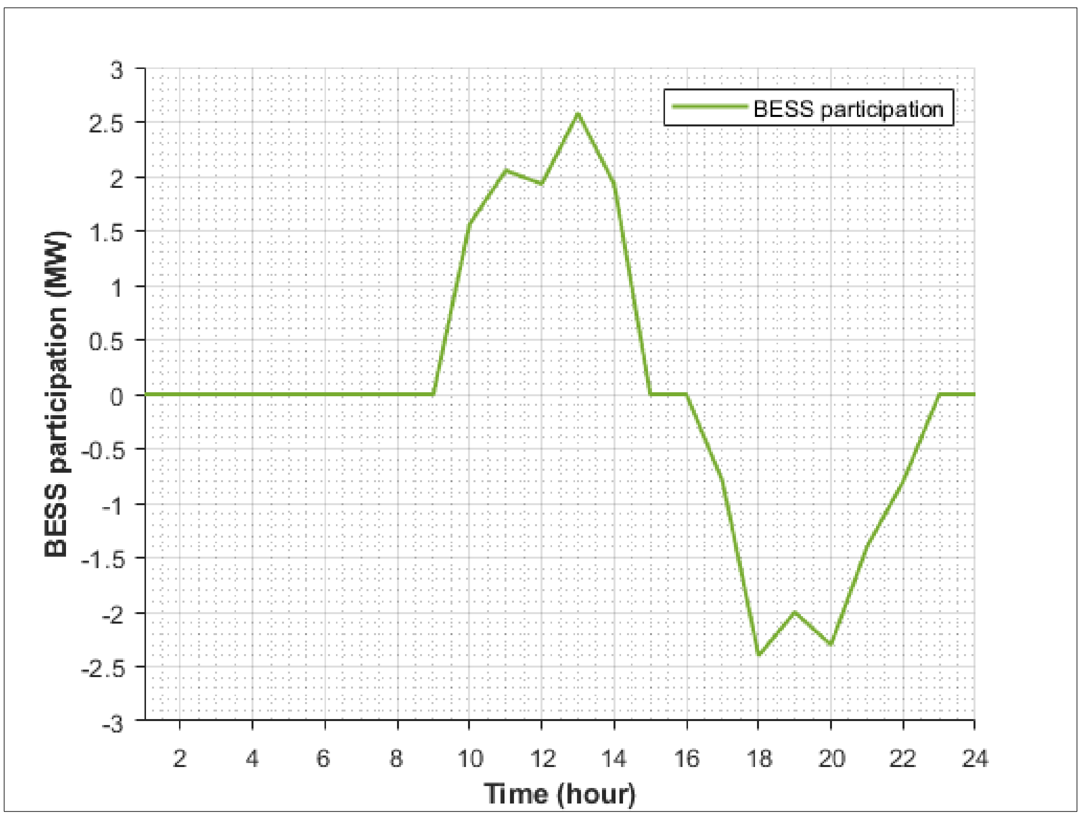

Figure 3.9 Charging discharging rate (MW) for each BESS in 141-bus system

It was observed that power loss increased during charging hours and decreased during discharging hours. The optimal time to discharge BESSs was found to be during peak hours when electricity demand spikes, leading to an increase in active power loss. Figure 3.9 displays the participation rate of BESSs and provides a visual representation of their charge and discharge in MW over a 24-hour period. The figure shows that the PJ-ADMM algorithm evenly distributes power based on each BESS's capacity, with each BESS charging approximately 2.5 MW at 13:00 and reaching a total charging power of 7.7 MW for all three BESSs, which represents the discharged energy amount at hour 18. This study highlights the importance of incorporating storage systems, such as BESS, into power systems with high PV penetration to reduce energy loss and improve overall system performance.

Table 3.2 presents a clear correlation between the rise in PV power generation and the increased capacity of BESS. The data demonstrates that for every 10% increase in PV generation at 13:00, there is approximately a 30% increase in BESS capacity. This strong positive relationship between rising PV power generation and BESS capacity emphasizes the significance of incorporating BESS into renewable energy systems to enhance their overall efficiency and performance. For example, the data shows that with the installation of 38 PV units and a 3.4 MWh BESS capacity, there is a 30% increase in BESS capacity compared to the case of 35 PV installations. This highlights the benefits of incorporating BESS into renewable energy systems to effectively manage and store excess energy generated by PV units. Overall, Table 4.2 provides compelling evidence of the crucial role that BESS plays in maximizing the potential of renewable energy systems.

Table 3.2 Power loss reduction with BESs

Number of PV in the system	**Power Generation (MW)**	**BESS capacity (MWh)**
35	21	2.5
38	23	3.4

Figure 3.10 provides a visual representation of the voltage convergence performance at node 29 at 13:00 for a smart inverter. To assess the impact of network size on the performance of the control algorithm, a comparison was made between the 33-bus and 141-bus networks. The results in the 141-bus network indicated that the PJ-ADMM algorithm with BESS converged

to the optimal solution relatively quickly, reaching it after approximately 14 iterations. In contrast, the 33-bus network required only 10 iterations to reach the optimal solution. This observation suggests that the increase in the number of agents does not necessarily result in a proportional increase in the number of iterations required for convergence.

Each iteration of the JP-ADMM control took about 3 seconds, and the case studies revealed that the JP-ADMM took approximately 0.5 minutes (10 iterations) in the 33-bus network and 0.75 minutes (14 iterations) in the 141-bus network to converge voltage at each bus to its limits. Although the increase in the system's size and the corresponding increase in the number of iterations led to an increase in calculation time, the JP-ADMM method still maintained a reasonable convergence rate. This highlights the effectiveness and importance of this method, as the increase in the number of agents was not proportional to the increase in the number of iterations required for convergence.

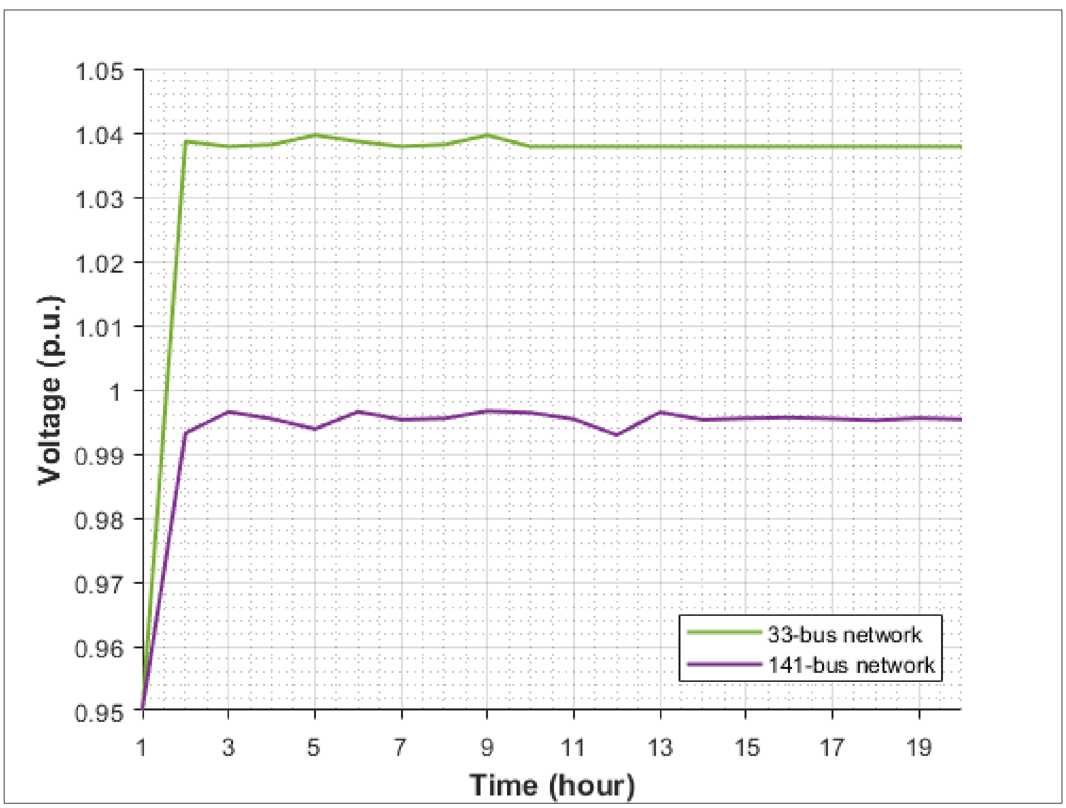

Figure 3.10 Voltage convergence at node 29 at 13:00

The proposed voltage control model was rigorously evaluated to determine its effectiveness. To do this, a comparison was made between the results obtained from the proposed model and those obtained from the default profile without control. The results of the comparison were visualized in Figure 3.11 and provided conclusive evidence of the success of the proposed model in reducing energy losses. The results showed that using BESSs, either through a distributed control approach or a centralized control approach, produced the same optimal solution in voltage regulation. This highlights the versatility and effectiveness of the proposed model in achieving the desired outcome of stable and efficient voltage regulation. Overall, the results of the comparison clearly demonstrate the superiority of the proposed voltage control model over the default profile without control. It effectively reduces energy losses and provides the same optimal solution in voltage regulation, regardless of the control approach used.

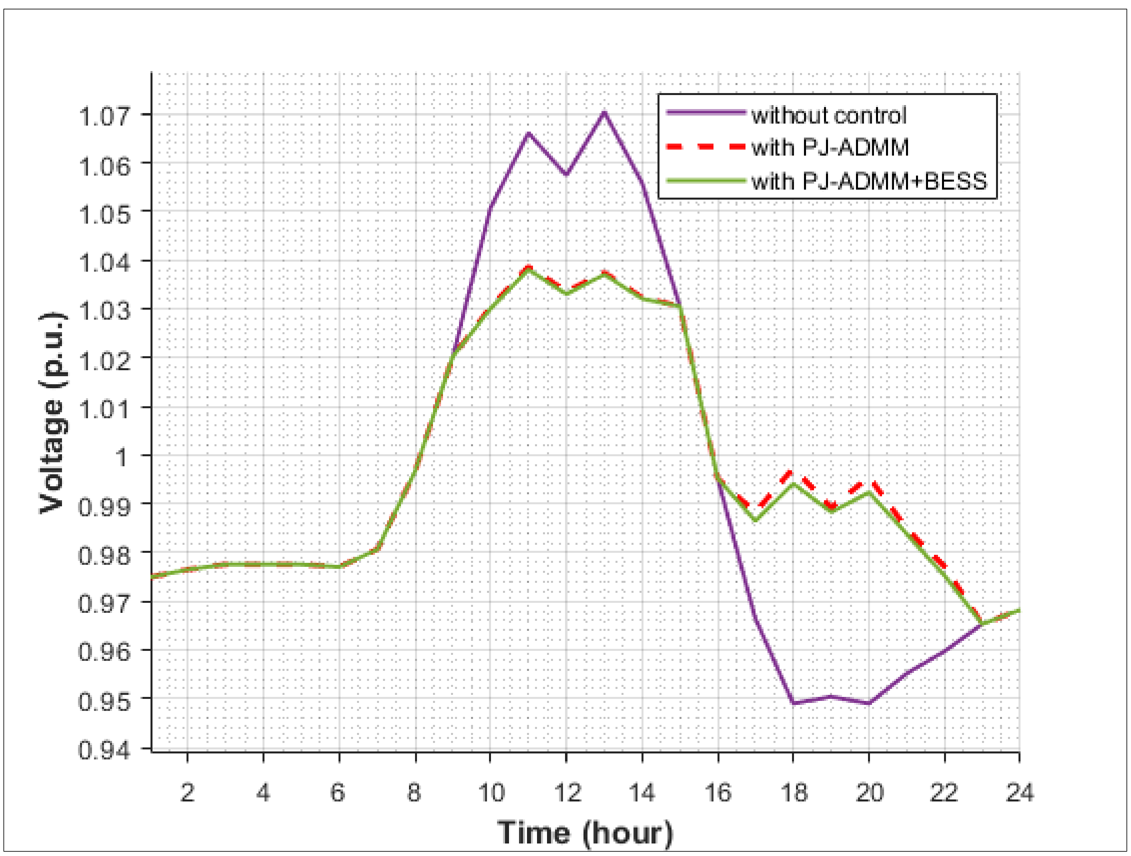

Figure 3.11 Voltage profile with and without control compared with BESS at node 28

3.4 Conclusion

This study proposed an optimal active/reactive power control for intelligent inverters to mitigate the voltage violation problem in distribution networks with high PV penetration. This scheme uses a fully distributed control strategy based on the PJ-ADMM algorithm to coordinate the PV inverters and virtual batteries for voltage regulation. Coupling smart PV inverter features and BESS ensures voltage regulation within feasible bands without power loss. The participating smart inverter needs to solve the control functions including active power generation and consumption at each node for voltage regulation. The control policies help assign storage capacity and estimate the minimum amount of power needed to be absorbed by storage from excess PV generation without PV power curtailment. Thus, the idea of storage sizing comes from a virtual curtailment strategy through the PJ-ADMM algorithm cycle by modifying the storage participation in voltage regulation, which gives rise to the efficient utilization of the BESS capability during power imbalance periods. The proposed algorithm was validated using IEEE 33-bus and 141-bus test feeders under different scenarios using MATPOWER. The simulation results validate that the strategy can maintain the profile voltages within the considered constraints and minimize the PV power loss, which verifies the effectiveness, robustness and scalability of the control scheme.

CONCLUSIONS AND RECOMMENDATIONS

This chapter concludes the work and introduces future works and opportunities to further research that could address further the requirements in this topic. This work mainly focused on the voltage regulation of distribution systems. This dissertation proposes through new techniques the optimal coordination of the PV inverters and BESS in the distribution network to improve voltage regulation on the buses and reduce power losses using an intelligent distributed control algorithm on distribution networks with variable and unbalanced loads.
Global demand for electrical energy is rising fast over the decades. Using sustainable renewable energy technologies in power grids is a key solution to overcoming climate change disasters and reducing greenhouse gas emissions. The growing demand for deploying DERs presents some challenges in the control of distribution networks. Future distribution networks are expected to host thousands of DERs and loads. High levels of integrating distributed photovoltaic energy sources in low voltage distribution networks bring a set of serious voltage challenges, such as the violations of grid voltage levels due to reverse power flow. In this study, we attempted to address the challenges of distribution systems.

Conclusion

The traditional centralized control networks were often suffering from instabilities and uncertainty. In this context intelligent distributed management is required that can potentially overcome the complexity of operating distribution networks. Hence, developing a reliable, and efficient solution methodology to cope with the high integration of RESs has become a matter of great interest. There have been many solutions proposed to overcome the voltage challenges by applying some features provided by new versions of smart inverters such as active power control and reactive power compensation. One of the most effective solutions to the voltage rise issue is managing active power through BESS. This solution enables consumers to maximize their PV power use, considering energy generation and load uncertainty.

This thesis highlights the necessity for identifying the impact of developing a new concept of grid voltage support function provided by smart PV inverters and BESS to mitigate voltage violation problems on distribution networks. Also developing intelligent optimization techniques to overcome the complexity of operating distribution networks with high-PV penetration reliably and optimally. The impact of uncertainties associated with load; renewable generation is investigated in this thesis. In this study, we focus on the distributed control scheme to obtain an optimal utilization of the PV power by controlling the PV inverters locally through the PJ-ADMM algorithm in cooperation with the BESS due to minimizing the PV power loss. To reach this goal, an optimization-based distributed control scheme is proposed. The participating smart inverter needs to solve the control functions including active and reactive power generation and consumption at each node for voltage regulation.

The proposed method determines the optimal sizing of BESSs in the distribution network which minimizes power loss. The control policies help assign storage capacity and estimate the minimum amount of power needed to be absorbed by storage from excess PV generation without PV power curtailment. Thus, the idea of storage sizing comes from a virtual curtailment strategy through the PJ-ADMM algorithm cycle by modifying the storage participation in voltage regulation, which gives rise to the efficient utilization of the BESS capability during power imbalance periods.

We applied mathematical approaches such as optimization techniques and distributed computation algorithms, to formulate, and solve the voltage regulation problem. A parallel multi-block ADMM (the so-called Jacobi ADMM) is developed by adding the proximal terms for each sub-problem for accelerating voltage convergence. To propose a robust configuration of a control scheme in the presence of uncertainties associated with load, and power generation, a control scheme for PV-battery systems to provide voltage control is formulated to allocate the active power capacity of each storage to compute the minimum amount of required curtailment and minimize the power loss. Two methodologies were proposed in this thesis for voltage control using developed PJ-ADMM. We developed a distributed MAS-based voltage control system through an optimization algorithm for smart PV inverters of distribution system to minimize the active power curtailment and reactive power compensation The first phase of this work was based on distributed optimization of smart PV inverters, in which an iterative decomposition algorithm is developed to implement an optimization-based voltage control system, while the second phase is based on a robust coordinated control scheme using BESS.

This objective was accomplished by formulating a multi-agent decomposition algorithm to compute the minimum amount of the active and reactive powers of the PVs at each agent to maintain the grid voltage within the limits. The agents coordinate using the PJ-ADMM algorithm. The results are compared with the voltage profiles from the case of no voltage control which showed the good performance of the algorithm in terms of convergence speed. The method controls the PV units' voltage in a MAS-based voltage regulation framework in a distribution network with high PV penetration. The result indicated that the proposed control strategy is capable of solving the control problem with fast convergence.

The second phase consists in investigating the role of BESS in minimizing losses and regulating voltage profiles using the optimal coordinated control method. The voltage support functions of smart inverters compute the amount of active power and battery power needed to maintain voltages within acceptable limits. The voltage support functions are responsible to determine how much power of each PV unit should be curtailed to maintain the voltage profiles within the limits. The storage can later release the stored energy when the electricity demand is high. This method will save PV generation, shave the peak demand, and benefit the consumer's revenue.

The effectiveness of the proposed method was validated on the modified IEEE 13-node test feeder, IEEE 33-node and 141-node and test feeders on MATLAB. The power flow analysis was provided using open-source software called MATPOWER. Load and generation variables are applied over 24 hours. The robustness and scalability of the proposed method was confirmed by implementing twenty PVs on the 141-bus distribution network. Simulation results show that the developed algorithm can maintain the voltage profiles within acceptable constraints and reduce power losses using BESS.

Recommendations

This thesis focused on developing a fully decentralized voltage control methodology utilizing the PJ-ADMM algorithm for determining the charging/discharging control actions for BESs. The studies presented in this thesis are limited to specific methodology and parameters, which facilitate the expansion of the research scope. Based on the work presented in this thesis, future research can be extended in the following research directions.

- Extension of the proposed method to create a scalable platform that integrates different renewable energy sources, energy storage systems, and electric vehicles and facilitates communication among them through a sophisticated control system.
- Development of a real-time algorithm that assesses the performance of the proposed method in real-world conditions and applications.
- Extend the algorithm to encompass single-phase PV inverter networks.
- Examination of the impact of reactive power regulations on the frequency control of the system.
- Investigation of the use of BESS for reactive power control in coordination with smart PV inverters.
- Develop and implementation of an intelligent method for training agents using neural networks, which would reduce the running time of distributed ADMM algorithms.
  Development of a cost-effective solution for maintaining voltage stability in the system under uncertainties during transmission level.

APPENDIX I

DETAILS OF THE TEST SYSTEMS

In this Appendix, the detailed test systems and data are presented to help readers understand the performance of the proposed method and to replicate the results reported in the main text.

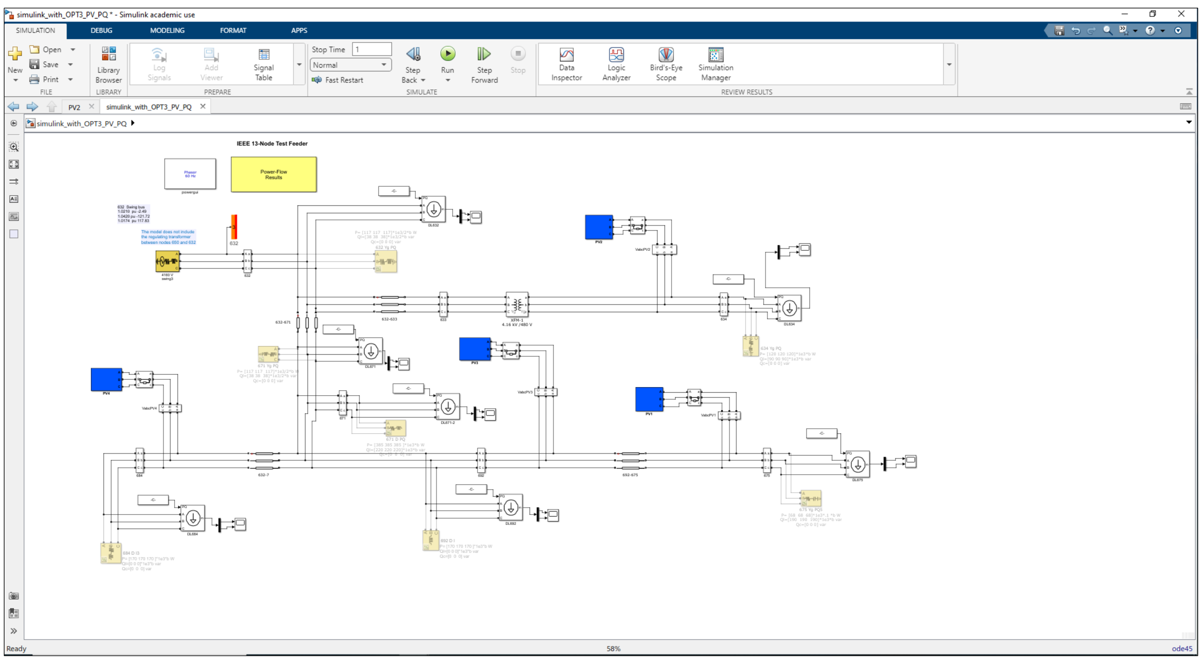

Figure-A I-1 Modified model of the IEEE 13-node test feeder on Simulink-MATLAB

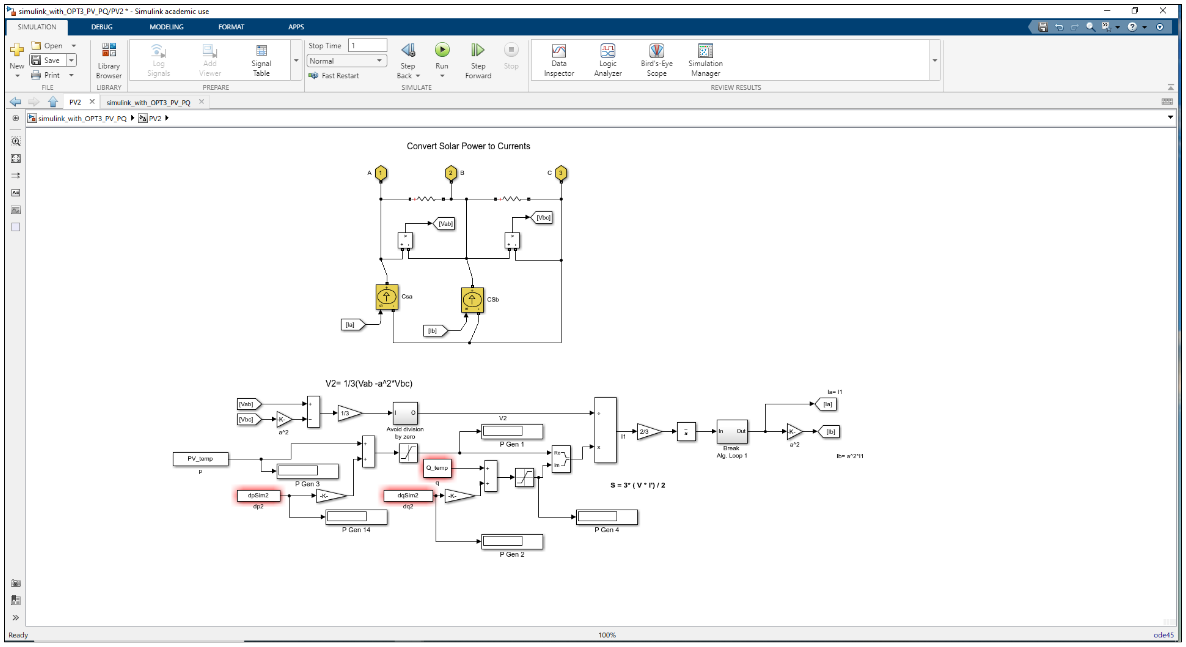

Figure-A I-2 Block diagram of the PV controller

Detailed data of the IEEE 33-node test feeder on Matpower


```
function mpc = case33bw
%CASE33BW  Power flow data for 33 bus distribution system from Baran & Wu
%   Please see CASEFORMAT for details on the case file format.
%
%   Data from ...
%       M. E. Baran and F. F. Wu, "Network reconfiguration in distribution
%       systems for loss reduction and load balancing," in IEEE Transactions
%       on Power Delivery, vol. 4, no. 2, pp. 1401-1407, Apr 1989.
%       doi: 10.1109/61.25627
%       URL: https://doi.org/10.1109/61.25627

%% MATPOWER Case Format : Version 2
mpc.version = '2';

%%-----  Power Flow Data  -----%%
%% system MVA base
mpc.baseMVA = 10;

%% bus data
%   bus_i   type    Pd  Qd  Gs  Bs  area    Vm  Va  baseKV  zone    Vmax    Vmin
mpc.bus = [ %% (Pd and Qd are specified in kW & kVAr here, converted to MW & MVAr below)
    1   3   0   0   0   0   1   1   0   12.66   1   1   1;
    2   1   100 60  0   0   1   1   0   12.66   1   1.1 0.9;
    3   1   90  40  0   0   1   1   0   12.66   1   1.1 0.9;
    4   1   120 80  0   0   1   1   0   12.66   1   1.1 0.9;
    5   1   60  30  0   0   1   1   0   12.66   1   1.1 0.9;
    6   1   60  20  0   0   1   1   0   12.66   1   1.1 0.9;
    7   1   200 100 0   0   1   1   0   12.66   1   1.1 0.9;
    8   1   200 100 0   0   1   1   0   12.66   1   1.1 0.9;
    9   1   60  20  0   0   1   1   0   12.66   1   1.1 0.9;
    10  1   60  20  0   0   1   1   0   12.66   1   1.1 0.9;
    11  1   45  30  0   0   1   1   0   12.66   1   1.1 0.9;
    12  1   60  35  0   0   1   1   0   12.66   1   1.1 0.9;
    13  1   60  35  0   0   1   1   0   12.66   1   1.1 0.9;
    14  1   120 80  0   0   1   1   0   12.66   1   1.1 0.9;
    15  1   60  10  0   0   1   1   0   12.66   1   1.1 0.9;
    16  1   60  20  0   0   1   1   0   12.66   1   1.1 0.9;
    17  1   60  20  0   0   1   1   0   12.66   1   1.1 0.9;
    18  1   90  40  0   0   1   1   0   12.66   1   1.1 0.9;
    19  1   90  40  0   0   1   1   0   12.66   1   1.1 0.9;
    20  1   90  40  0   0   1   1   0   12.66   1   1.1 0.9;
    21  1   90  40  0   0   1   1   0   12.66   1   1.1 0.9;
    22  1   90  40  0   0   1   1   0   12.66   1   1.1 0.9;
    23  1   90  50  0   0   1   1   0   12.66   1   1.1 0.9;
    24  1   420 200 0   0   1   1   0   12.66   1   1.1 0.9;
    25  1   420 200 0   0   1   1   0   12.66   1   1.1 0.9;
    26  1   60  25  0   0   1   1   0   12.66   1   1.1 0.9;
    27  1   60  25  0   0   1   1   0   12.66   1   1.1 0.9;
    28  1   60  20  0   0   1   1   0   12.66   1   1.1 0.9;
    29  1   120 70  0   0   1   1   0   12.66   1   1.1 0.9;
    30  1   200 600 0   0   1   1   0   12.66   1   1.1 0.9;
```

```
    31  1   150 70  0   0   1   1   0   12.66   1   1.1 0.9;
    32  1   210 100 0   0   1   1   0   12.66   1   1.1 0.9;
    33  1   60  40  0   0   1   1   0   12.66   1   1.1 0.9;
];

%% generator data
%   bus Pg  Qg  Qmax    Qmin    Vg  mBase   status  Pmax    Pmin    Pc1 Pc2 Qc1min
Qc1max  Qc2min  Qc2max  ramp_agc    ramp_10 ramp_30 ramp_q  apf
mpc.gen = [
    1   0   0   10  -10 1   100 1   10  0   0   0   0   0   0   0   0   0   0   0   0;
];

%% branch data
%   fbus    tbus    r   x   b   rateA   rateB   rateC   ratio   angle   status  angmin
angmax
mpc.branch = [  %% (r and x specified in ohms here, converted to p.u. below)
    1   2   0.0922  0.0470  0   0   0   0   0   0   1   -360    360;
    2   3   0.4930  0.2511  0   0   0   0   0   0   1   -360    360;
    3   4   0.3660  0.1864  0   0   0   0   0   0   1   -360    360;
    4   5   0.3811  0.1941  0   0   0   0   0   0   1   -360    360;
    5   6   0.8190  0.7070  0   0   0   0   0   0   1   -360    360;
    6   7   0.1872  0.6188  0   0   0   0   0   0   1   -360    360;
    7   8   0.7114  0.2351  0   0   0   0   0   0   1   -360    360;
    8   9   1.0300  0.7400  0   0   0   0   0   0   1   -360    360;
    9   10  1.0440  0.7400  0   0   0   0   0   0   1   -360    360;
    10  11  0.1966  0.0650  0   0   0   0   0   0   1   -360    360;
    11  12  0.3744  0.1238  0   0   0   0   0   0   1   -360    360;
    12  13  1.4680  1.1550  0   0   0   0   0   0   1   -360    360;
    13  14  0.5416  0.7129  0   0   0   0   0   0   1   -360    360;
    14  15  0.5910  0.5260  0   0   0   0   0   0   1   -360    360;
    15  16  0.7463  0.5450  0   0   0   0   0   0   1   -360    360;
    16  17  1.2890  1.7210  0   0   0   0   0   0   1   -360    360;
    17  18  0.7320  0.5740  0   0   0   0   0   0   1   -360    360;
    2   19  0.1640  0.1565  0   0   0   0   0   0   1   -360    360;
    19  20  1.5042  1.3554  0   0   0   0   0   0   1   -360    360;
    20  21  0.4095  0.4784  0   0   0   0   0   0   1   -360    360;
    21  22  0.7089  0.9373  0   0   0   0   0   0   1   -360    360;
    3   23  0.4512  0.3083  0   0   0   0   0   0   1   -360    360;
    23  24  0.8980  0.7091  0   0   0   0   0   0   1   -360    360;
    24  25  0.8960  0.7011  0   0   0   0   0   0   1   -360    360;
    6   26  0.2030  0.1034  0   0   0   0   0   0   1   -360    360;
    26  27  0.2842  0.1447  0   0   0   0   0   0   1   -360    360;
    27  28  1.0590  0.9337  0   0   0   0   0   0   1   -360    360;
    28  29  0.8042  0.7006  0   0   0   0   0   0   1   -360    360;
    29  30  0.5075  0.2585  0   0   0   0   0   0   1   -360    360;
    30  31  0.9744  0.9630  0   0   0   0   0   0   1   -360    360;
    31  32  0.3105  0.3619  0   0   0   0   0   0   1   -360    360;
    32  33  0.3410  0.5302  0   0   0   0   0   0   1   -360    360;
    21  8   2.0000  2.0000  0   0   0   0   0   0   0   -360    360;
    9   15  2.0000  2.0000  0   0   0   0   0   0   0   -360    360;
    12  22  2.0000  2.0000  0   0   0   0   0   0   0   -360    360;
```

```
    18  33  0.5000  0.5000  0   0   0   0   0   0   0   -360    360;
    25  29  0.5000  0.5000  0   0   0   0   0   0   0   -360    360;
];

%%-----  OPF Data  -----%%
%% generator cost data
%   1   startup shutdown    n   x1  y1  ... xn  yn
%   2   startup shutdown    n   c(n-1)  ... c0
mpc.gencost = [
    2   0   0   3   0   20  0;
];


%% convert branch impedances from Ohms to p.u.
[PQ, PV, REF, NONE, BUS_I, BUS_TYPE, PD, QD, GS, BS, BUS_AREA, VM, ...
    VA, BASE_KV, ZONE, VMAX, VMIN, LAM_P, LAM_Q, MU_VMAX, MU_VMIN] = idx_bus;
[F_BUS, T_BUS, BR_R, BR_X, BR_B, RATE_A, RATE_B, RATE_C, ...
    TAP, SHIFT, BR_STATUS, PF, QF, PT, QT, MU_SF, MU_ST, ...
    ANGMIN, ANGMAX, MU_ANGMIN, MU_ANGMAX] = idx_brch;
Vbase = mpc.bus(1, BASE_KV) * 1e3;      %% in Volts
Sbase = mpc.baseMVA * 1e6;              %% in VA
mpc.branch(:, [BR_R BR_X]) = mpc.branch(:, [BR_R BR_X]) / (Vbase^2 / Sbase);

%% convert loads from kW to MW
mpc.bus(:, [PD, QD]) = mpc.bus(:, [PD, QD]) / 1e3;
```

Detailed data of the IEEE 141-node test feeder on Matpower


```
function mpc = case141
%CASE141  Power flow data for 141 bus distribution system
%   Please see CASEFORMAT for details on the case file format.
%
%   Data from ...
%       H.M. Khodr, F.G. Olsina, P.M. De Oliveira-De Jesus, J.M. Yusta,
%       Maximum savings approach for location and sizing of capacitors in
%       distribution systems, Electric Power Systems Research, Volume 78,
%       Issue 7, July 2008, Pages 1192-1203
%       https://doi.org/10.1016/j.epsr.2007.10.002
%
%   Covers "a zone of the metropolitan area of Caracas" in Venezuela.
%
%   The data in the paper includes numerous typos, including the following
%   which were corrected based on the one-line diagram.
%       - branch 17--10 should be 17--18
%       - branch 16--19 should be 18--19
%       - branch 27--23 should be 27--28
%       - branch 27--26 should be 25--26
%       - branch 67--63 should be 67--68
%       - branch 66--70 should be 55--70
%       - branch 16--137 should be 18--137
%
%   Modifications:
%     v2 - 2020-10-01 (RDZ)
%         - Specify branch parameters in Ohms, loads in kVA.
%         - Added code for explicit conversion of loads from kVA
%           to MVA, then from MVA and power factor to MW and MVAr, and
%           of branch parameters from Ohms to p.u.
%         - Doubled load at bus 53 (100 kVA instead of 50 kVA)
%         - Set BASE_KV to 12.47 kV (instead of 12.5)
%         - Branch order as in paper (rather than sorted by from bus)
%         - Slack bus Vmin = Vmax = 1.0
%         - Gen Qmin, Qmax, Pmax magnitudes set to 100 (instead of 999)
%         - Branch flow limits disabled, i.e. set to 0 (instead of 999)
%         - Add gen cost.


%% MATPOWER Case Format : Version 2
mpc.version = '2';

%%-----  Power Flow Data  -----%%
%% system MVA base
mpc.baseMVA = 10;

%% bus data
%   bus_i   type    Pd  Qd  Gs  Bs  area    Vm  Va  baseKV  zone    Vmax    Vmin
mpc.bus = [ %% (Pd is specified in kVA here for 0.85 power factor, converted to MW & MVAr
below)
    1   3   0   0   0   0   1   1   0   12.47   1   1   1;
    2   1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
```

```
    3   1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    4   1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    5   1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    6   1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    7   1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    8   1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    9   1   10  0   0   0   1   1   0   12.47   1   1.1 0.9;
    10  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    11  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    12  1   25  0   0   0   1   1   0   12.47   1   1.1 0.9;
    13  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    14  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    15  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    16  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    17  1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    18  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    19  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    20  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    21  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    22  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    23  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    24  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    25  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    26  1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    27  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    28  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    29  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    30  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    31  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    32  1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    33  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    34  1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    35  1   300 0   0   0   1   1   0   12.47   1   1.1 0.9;
    36  1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    37  1   50  0   0   0   1   1   0   12.47   1   1.1 0.9;
    38  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    39  1   20  0   0   0   1   1   0   12.47   1   1.1 0.9;
    40  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    41  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    42  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    43  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    44  1   50  0   0   0   1   1   0   12.47   1   1.1 0.9;
    45  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    46  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    47  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    48  1   125 0   0   0   1   1   0   12.47   1   1.1 0.9;
    49  1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    50  1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    51  1   125 0   0   0   1   1   0   12.47   1   1.1 0.9;
    52  1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    53  1   100 0   0   0   1   1   0   12.47   1   1.1 0.9;
```

```
    54  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    55  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    56  1   25   0   0   0   1   1   0   12.47   1   1.1 0.9;
    57  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    58  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    59  1   150  0   0   0   1   1   0   12.47   1   1.1 0.9;
    60  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    61  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    62  1   200  0   0   0   1   1   0   12.47   1   1.1 0.9;
    63  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    64  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    65  1   150  0   0   0   1   1   0   12.47   1   1.1 0.9;
    66  1   225  0   0   0   1   1   0   12.47   1   1.1 0.9;
    67  1   50   0   0   0   1   1   0   12.47   1   1.1 0.9;
    68  1   100  0   0   0   1   1   0   12.47   1   1.1 0.9;
    69  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    70  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    71  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    72  1   150  0   0   0   1   1   0   12.47   1   1.1 0.9;
    73  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    74  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    75  1   45   0   0   0   1   1   0   12.47   1   1.1 0.9;
    76  1   75   0   0   0   1   1   0   12.47   1   1.1 0.9;
    77  1   150  0   0   0   1   1   0   12.47   1   1.1 0.9;
    78  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    79  1   502.5   0   0   0   1   1   0   12.47   1   1.1 0.9;
    80  1   750  0   0   0   1   1   0   12.47   1   1.1 0.9;
    81  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    82  1   150  0   0   0   1   1   0   12.47   1   1.1 0.9;
    83  1   75   0   0   0   1   1   0   12.47   1   1.1 0.9;
    84  1   225  0   0   0   1   1   0   12.47   1   1.1 0.9;
    85  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    86  1   500  0   0   0   1   1   0   12.47   1   1.1 0.9;
    87  1   150  0   0   0   1   1   0   12.47   1   1.1 0.9;
    88  1   75   0   0   0   1   1   0   12.47   1   1.1 0.9;
    89  1   65   0   0   0   1   1   0   12.47   1   1.1 0.9;
    90  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    91  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    92  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    93  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    94  1   110  0   0   0   1   1   0   12.47   1   1.1 0.9;
    95  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    96  1   150  0   0   0   1   1   0   12.47   1   1.1 0.9;
    97  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    98  1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    99  1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    100 1   300  0   0   0   1   1   0   12.47   1   1.1 0.9;
    101 1   15   0   0   0   1   1   0   12.47   1   1.1 0.9;
    102 1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
    103 1   125  0   0   0   1   1   0   12.47   1   1.1 0.9;
    104 1   0    0   0   0   1   1   0   12.47   1   1.1 0.9;
```

```
    105 1   300 0   0   0   1   1   0   12.47   1   1.1 0.9;
    106 1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    107 1   502.5   0   0   0   1   1   0   12.47   1   1.1 0.9;
    108 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    109 1   750 0   0   0   1   1   0   12.47   1   1.1 0.9;
    110 1   750 0   0   0   1   1   0   12.47   1   1.1 0.9;
    111 1   25  0   0   0   1   1   0   12.47   1   1.1 0.9;
    112 1   500 0   0   0   1   1   0   12.47   1   1.1 0.9;
    113 1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    114 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    115 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    116 1   300 0   0   0   1   1   0   12.47   1   1.1 0.9;
    117 1   65  0   0   0   1   1   0   12.47   1   1.1 0.9;
    118 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    119 1   110 0   0   0   1   1   0   12.47   1   1.1 0.9;
    120 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    121 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    122 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    123 1   100 0   0   0   1   1   0   12.47   1   1.1 0.9;
    124 1   125 0   0   0   1   1   0   12.47   1   1.1 0.9;
    125 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    126 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    127 1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    128 1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    129 1   110 0   0   0   1   1   0   12.47   1   1.1 0.9;
    130 1   112.5   0   0   0   1   1   0   12.47   1   1.1 0.9;
    131 1   0   0   0   0   1   1   0   12.47   1   1.1 0.9;
    132 1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    133 1   45  0   0   0   1   1   0   12.47   1   1.1 0.9;
    134 1   35  0   0   0   1   1   0   12.47   1   1.1 0.9;
    135 1   25  0   0   0   1   1   0   12.47   1   1.1 0.9;
    136 1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
    137 1   55  0   0   0   1   1   0   12.47   1   1.1 0.9;
    138 1   50  0   0   0   1   1   0   12.47   1   1.1 0.9;
    139 1   50  0   0   0   1   1   0   12.47   1   1.1 0.9;
    140 1   150 0   0   0   1   1   0   12.47   1   1.1 0.9;
    141 1   75  0   0   0   1   1   0   12.47   1   1.1 0.9;
];

%% generator data
%   bus Pg  Qg  Qmax    Qmin    Vg  mBase   status  Pmax    Pmin    Pc1 Pc2 Qc1min
Qc1max  Qc2min  Qc2max  ramp_agc    ramp_10 ramp_30 ramp_q  apf
mpc.gen = [
    1   0   0   100 -100    1   100 1   100 0   0   0   0   0   0   0   0   0   0   0
0;
];

%% branch data
%   fbus    tbus    r   x   b   rateA   rateB   rateC   ratio   angle   status  angmin
angmax
mpc.branch = [  %% (r and x specified in ohms here, converted to p.u. below)
```

```
1   2   0.0577  0.0409  0   0   0   0   0   0   1   -360    360;
2   3   0.1725  0.1223  0   0   0   0   0   0   1   -360    360;
3   4   0.0009  0.0006  0   0   0   0   0   0   1   -360    360;
4   5   0.0092  0.0065  0   0   0   0   0   0   1   -360    360;
5   6   0.0068  0.0049  0   0   0   0   0   0   1   -360    360;
6   7   0.0469  0.0625  0   0   0   0   0   0   1   -360    360;
7   8   0.0736  0.0981  0   0   0   0   0   0   1   -360    360;
8   9   0.0649  0.0459  0   0   0   0   0   0   1   -360    360;
9   10  0.0507  0.0359  0   0   0   0   0   0   1   -360    360;
10  11  0.0116  0.0082  0   0   0   0   0   0   1   -360    360;
11  12  0.1291  0.0913  0   0   0   0   0   0   1   -360    360;
12  13  0.1227  0.0866  0   0   0   0   0   0   1   -360    360;
13  14  0.0488  0.0345  0   0   0   0   0   0   1   -360    360;
14  15  0.0957  0.0677  0   0   0   0   0   0   1   -360    360;
15  16  0.086   0.0609  0   0   0   0   0   0   1   -360    360;
16  17  0.0398  0.0282  0   0   0   0   0   0   1   -360    360;
17  18  0.0828  0.0566  0   0   0   0   0   0   1   -360    360;
18  19  0.0186  0.0132  0   0   0   0   0   0   1   -360    360;
19  20  0.0559  0.0395  0   0   0   0   0   0   1   -360    360;
20  21  0.0365  0.0246  0   0   0   0   0   0   1   -360    360;
21  22  0.0573  0.0307  0   0   0   0   0   0   1   -360    360;
22  23  0.0263  0.0191  0   0   0   0   0   0   1   -360    360;
23  24  0.0683  0.0497  0   0   0   0   0   0   1   -360    360;
24  25  0.0398  0.0282  0   0   0   0   0   0   1   -360    360;
25  26  0.0729  0.053   0   0   0   0   0   0   1   -360    360;
26  27  0.0335  0.0244  0   0   0   0   0   0   1   -360    360;
27  28  0.0584  0.0414  0   0   0   0   0   0   1   -360    360;
28  29  0.0655  0.0463  0   0   0   0   0   0   1   -360    360;
61  62  0.0411  0.0291  0   0   0   0   0   0   1   -360    360;
60  63  0.0353  0.025   0   0   0   0   0   0   1   -360    360;
63  64  0.1047  0.0741  0   0   0   0   0   0   1   -360    360;
64  65  0.0674  0.0477  0   0   0   0   0   0   1   -360    360;
65  66  0.0302  0.0214  0   0   0   0   0   0   1   -360    360;
66  67  0.0456  0.0323  0   0   0   0   0   0   1   -360    360;
67  68  0.0218  0.0154  0   0   0   0   0   0   1   -360    360;
70  72  0.07    0.0495  0   0   0   0   0   0   1   -360    360;
42  73  0.0231  0.0164  0   0   0   0   0   0   1   -360    360;
73  74  0.003   0.0064  0   0   0   0   0   0   1   -360    360;
43  75  0.0379  0.0268  0   0   0   0   0   0   1   -360    360;
44  76  0.0552  0.0391  0   0   0   0   0   0   1   -360    360;
46  77  0.0516  0.0436  0   0   0   0   0   0   1   -360    360;
76  78  0.0167  0.011   0   0   0   0   0   0   1   -360    360;
78  79  0.0415  0.0101  0   0   0   0   0   0   1   -360    360;
79  80  0.1003  0.0244  0   0   0   0   0   0   1   -360    360;
79  81  0.1513  0.037   0   0   0   0   0   0   1   -360    360;
81  82  0.0033  0.0008  0   0   0   0   0   0   1   -360    360;
47  83  0.0085  0.0062  0   0   0   0   0   0   1   -360    360;
49  84  0.0517  0.0449  0   0   0   0   0   0   1   -360    360;
50  85  0.0147  0.0036  0   0   0   0   0   0   1   -360    360;
85  86  0.0037  0.0016  0   0   0   0   0   0   1   -360    360;
86  87  0   0.00001 0   0   0   0   0   0   1   -360    360;
```

```
7   88  0.0174  0.0231  0   0   0   0   0   0   1   -360    360;
88  89  0.0469  0.0625  0   0   0   0   0   0   1   -360    360;
89  90  0.0299  0.0398  0   0   0   0   0   0   1   -360    360;
90  91  0.0212  0.0283  0   0   0   0   0   0   1   -360    360;
91  92  0.0315  0.042   0   0   0   0   0   0   1   -360    360;
92  93  0.028   0.0373  0   0   0   0   0   0   1   -360    360;
93  94  0.0206  0.0274  0   0   0   0   0   0   1   -360    360;
94  95  0.0206  0.0274  0   0   0   0   0   0   1   -360    360;
89  96  0.0687  0.0486  0   0   0   0   0   0   1   -360    360;
96  97  0.097   0.0686  0   0   0   0   0   0   1   -360    360;
97  98  0.0902  0.0196  0   0   0   0   0   0   1   -360    360;
97  99  0.0033  0.0008  0   0   0   0   0   0   1   -360    360;
131 132 0.0347  0.0245  0   0   0   0   0   0   1   -360    360;
131 133 0.092   0.0669  0   0   0   0   0   0   1   -360    360;
121 134 0.0841  0.0612  0   0   0   0   0   0   1   -360    360;
16  135 0.0527  0.0373  0   0   0   0   0   0   1   -360    360;
16  136 0.0302  0.0214  0   0   0   0   0   0   1   -360    360;
18  137 0.0584  0.0414  0   0   0   0   0   0   1   -360    360;
23  138 0.0769  0.0559  0   0   0   0   0   0   1   -360    360;
29  30  0.0342  0.0248  0   0   0   0   0   0   1   -360    360;
30  31  0.0128  0.0091  0   0   0   0   0   0   1   -360    360;
31  32  0.0347  0.0245  0   0   0   0   0   0   1   -360    360;
2   33  0.0443  0.0314  0   0   0   0   0   0   1   -360    360;
33  34  0.002   0.0009  0   0   0   0   0   0   1   -360    360;
5   35  0.2274  0.0554  0   0   0   0   0   0   1   -360    360;
5   36  0.1265  0.1565  0   0   0   0   0   0   1   -360    360;
6   37  0.0055  0.0073  0   0   0   0   0   0   1   -360    360;
37  38  0.2036  0.144   0   0   0   0   0   0   1   -360    360;
38  39  0.0938  0.0663  0   0   0   0   0   0   1   -360    360;
39  40  0.0347  0.0245  0   0   0   0   0   0   1   -360    360;
40  41  0.0918  0.065   0   0   0   0   0   0   1   -360    360;
41  42  0.2318  0.164   0   0   0   0   0   0   1   -360    360;
42  43  0.1207  0.0854  0   0   0   0   0   0   1   -360    360;
43  44  0.0443  0.0314  0   0   0   0   0   0   1   -360    360;
44  45  0.0405  0.0288  0   0   0   0   0   0   1   -360    360;
45  46  0.016   0.0127  0   0   0   0   0   0   1   -360    360;
46  47  0.0636  0.045   0   0   0   0   0   0   1   -360    360;
47  48  0.0417  0.0295  0   0   0   0   0   0   1   -360    360;
48  49  0.0732  0.051   0   0   0   0   0   0   1   -360    360;
49  50  0.0828  0.0556  0   0   0   0   0   0   1   -360    360;
50  51  0.0398  0.0282  0   0   0   0   0   0   1   -360    360;
51  52  0.0225  0.0159  0   0   0   0   0   0   1   -360    360;
38  53  0.0841  0.0595  0   0   0   0   0   0   1   -360    360;
42  54  0.0161  0.0114  0   0   0   0   0   0   1   -360    360;
54  55  0.0527  0.0373  0   0   0   0   0   0   1   -360    360;
55  56  0.0893  0.0632  0   0   0   0   0   0   1   -360    360;
56  57  0.0867  0.0613  0   0   0   0   0   0   1   -360    360;
57  58  0.0674  0.0477  0   0   0   0   0   0   1   -360    360;
58  59  0.0469  0.0332  0   0   0   0   0   0   1   -360    360;
55  60  0.0334  0.0236  0   0   0   0   0   0   1   -360    360;
60  61  0.0327  0.0232  0   0   0   0   0   0   1   -360    360;
```

```
    63  69  0.0366  0.0259  0   0   0   0   0   0   1   -360    360;
    55  70  0.0231  0.0164  0   0   0   0   0   0   1   -360    360;
    70  71  0.012   0.0029  0   0   0   0   0   0   1   -360    360;
    99  100 0.0033  0.0008  0   0   0   0   0   0   1   -360    360;
    91  101 0.0231  0.0164  0   0   0   0   0   0   1   -360    360;
    101 102 0.0578  0.0409  0   0   0   0   0   0   1   -360    360;
    102 103 0.0889  0.0217  0   0   0   0   0   0   1   -360    360;
    103 104 0.0629  0.0153  0   0   0   0   0   0   1   -360    360;
    104 105 0.117   0.0285  0   0   0   0   0   0   1   -360    360;
    104 106 0.0114  0.0026  0   0   0   0   0   0   1   -360    360;
    92  107 0.0849  0.0207  0   0   0   0   0   0   1   -360    360;
    94  108 0.0612  0.026   0   0   0   0   0   0   1   -360    360;
    108 109 0.0452  0.0192  0   0   0   0   0   0   1   -360    360;
    94  110 0.0033  0.0008  0   0   0   0   0   0   1   -360    360;
    7   111 0.0719  0.0509  0   0   0   0   0   0   1   -360    360;
    10  112 0.107   0.0261  0   0   0   0   0   0   1   -360    360;
    11  113 0.0347  0.0245  0   0   0   0   0   0   1   -360    360;
    13  114 0.0623  0.0441  0   0   0   0   0   0   1   -360    360;
    114 115 0.0668  0.0473  0   0   0   0   0   0   1   -360    360;
    115 116 0.004   0.001   0   0   0   0   0   0   1   -360    360;
    14  117 0.0506  0.0366  0   0   0   0   0   0   1   -360    360;
    15  118 0.0161  0.0114  0   0   0   0   0   0   1   -360    360;
    118 119 0.0462  0.0327  0   0   0   0   0   0   1   -360    360;
    119 120 0.0424  0.03    0   0   0   0   0   0   1   -360    360;
    120 121 0.0507  0.0359  0   0   0   0   0   0   1   -360    360;
    121 122 0.0732  0.0518  0   0   0   0   0   0   1   -360    360;
    122 123 0.0584  0.0414  0   0   0   0   0   0   1   -360    360;
    123 124 0.061   0.0432  0   0   0   0   0   0   1   -360    360;
    124 125 0.0783  0.0554  0   0   0   0   0   0   1   -360    360;
    125 126 0.0834  0.0607  0   0   0   0   0   0   1   -360    360;
    126 127 0.0347  0.0245  0   0   0   0   0   0   1   -360    360;
    127 128 0.057   0.042   0   0   0   0   0   0   1   -360    360;
    128 129 0.0585  0.0425  0   0   0   0   0   0   1   -360    360;
    129 130 0.0103  0.0073  0   0   0   0   0   0   1   -360    360;
    119 131 0.0355  0.0253  0   0   0   0   0   0   1   -360    360;
    25  139 0.095   0.0673  0   0   0   0   0   0   1   -360    360;
    30  140 0.0519  0.0377  0   0   0   0   0   0   1   -360    360;
    31  141 0.0584  0.0414  0   0   0   0   0   0   1   -360    360;
];

%%-----  OPF Data  -----%%
%% generator cost data
%   1   startup shutdown    n   x1  y1  ... xn  yn
%   2   startup shutdown    n   c(n-1)  ... c0
mpc.gencost = [
    2   0   0   3   0   20  0;
];


%% convert branch impedances from Ohms to p.u.
[PQ, PV, REF, NONE, BUS_I, BUS_TYPE, PD, QD, GS, BS, BUS_AREA, VM, ...
```

```
    VA, BASE_KV, ZONE, VMAX, VMIN, LAM_P, LAM_Q, MU_VMAX, MU_VMIN] = idx_bus;
[F_BUS, T_BUS, BR_R, BR_X, BR_B, RATE_A, RATE_B, RATE_C, ...
    TAP, SHIFT, BR_STATUS, PF, QF, PT, QT, MU_SF, MU_ST, ...
    ANGMIN, ANGMAX, MU_ANGMIN, MU_ANGMAX] = idx_brch;
Vbase = mpc.bus(1, BASE_KV) * 1e3;      %% in Volts
Sbase = mpc.baseMVA * 1e6;              %% in VA
mpc.branch(:, [BR_R BR_X]) = mpc.branch(:, [BR_R BR_X]) / (Vbase^2 / Sbase);

%% convert loads from kW to MW
mpc.bus(:, [PD, QD]) = mpc.bus(:, [PD, QD]) / 1e3;

%% convert loads from MVA to MW and MVAr, using 0.85 power factor
pf = 0.85;
mpc.bus(:, QD) = mpc.bus(:, PD) * sin(acos(pf));
mpc.bus(:, PD) = mpc.bus(:, PD) * pf;
```

LIST OF BIBLIOGRAPHICAL REFERENCES

Alam, M. J. E., Muttaqi, K. M., & Sutanto, D. (2015). Effective utilization of available PEV battery capacity for mitigation of solar PV impact and grid support with integrated V2G functionality. IEEE Transactions on Smart Grid, 7(3), 1562-1571.

Almasalma, H., Claeys, S., & Deconinck, G. (2019). Peer-to-peer-based integrated grid voltage support function for smart photovoltaic inverters. Applied energy, 239, 1037-1048.

Almasalma, H., & Deconinck, G. (2020). Robust policy-based distributed voltage control provided by PV-battery inverters. IEEE Access, 8, 124939-124948.

Almasalma, H., Engels, J., & Deconinck, G. (2017). Dual-decomposition-based peer-to-peer voltage control for distribution networks. arXiv preprint arXiv:1711.04055.

Alyami, S., Wang, Y., Wang, C., Zhao, J., & Zhao, B. (2014). Adaptive real power capping method for fair overvoltage regulation of distribution networks with high penetration of PV systems. IEEE Transactions on Smart Grid, 5(6), 2729-2738.

Amoroso, F. A., & Cappuccino, G. (2012). Advantages of efficiency-aware smart charging strategies for PEVs. Energy Conversion and Management, 54(1), 1-6.

Ananduta, W., Ocampo-Martinez, C., & Nedić, A. (2021). A Distributed Augmented Lagrangian Method over Stochastic Networks for Economic Dispatch of Large-Scale Energy Systems. IEEE Transactions on Sustainable Energy, 12(4), 1927-1934.

Andishgar, M. H., Gholipour, E., & Hooshmand, R.-a. (2017). An overview of control approaches of inverter-based microgrids in islanding mode of operation. Renewable and Sustainable Energy Reviews, 80, 1043-1060.

Antoniadou-Plytaria, K. E., Kouveliotis-Lysikatos, I. N., Georgilakis, P. S., & Hatziargyriou, N. D. (2017). Distributed and decentralized voltage control of smart distribution networks: Models, methods, and future research. IEEE Transactions on Smart Grid, 8(6), 2999-3008.

Arora, S., Satsangi, S., Kaur, S., & Khanna, R. (2021). Substation demand reduction by CVR enabled intelligent PV inverter control functions in distribution systems. International Transactions on Electrical Energy Systems, 31(2), e12724.

Ayyagari, K. S., Gatsis, N., & Taha, A. F. (2017). Chance constrained optimization of distributed energy resources via affine policies. In 2017 IEEE Global Conference on Signal and Information Processing (GlobalSIP) (pp. 1050-1054).

Aziz, S., Peng, J., Wang, H., & Jiang, H. (2019). Admm-based distributed optimization of hybrid mtdc-ac grid for determining smooth operation point. IEEE Access, 7, 74238-74247.

Aziz, T., & Ketjoy, N. (2017). Enhancing PV penetration in LV networks using reactive power control and on load tap changer with existing transformers. IEEE Access, 6, 2683-2691.

Babu, K. R., & Khatod, D. K. (2022). Improved Volt/Var Control Technique for Over-Voltage Mitigation. In 2022 Second International Conference on Power, Control and Computing Technologies (ICPC2T) (pp. 1-6).

Bahramipanah, M., Cherkaoui, R., & Paolone, M. (2016). Decentralized voltage control of clustered active distribution network by means of energy storage systems. Electric Power Systems Research, 136, 370-382.

Bai, F., Yan, R., Saha, T. K., & Eghbal, D. (2020). An excessive tap operation evaluation approach for unbalanced distribution networks with high PV penetration. IEEE Transactions on Sustainable Energy, 12(1), 169-178.

Bazrafshan, M., & Gatsis, N. (2016). Decentralized stochastic optimal power flow in radial networks with distributed generation. IEEE Transactions on Smart Grid, 8(2), 787-801.

Bidgoli, H. S., & Van Cutsem, T. (2017). Combined local and centralized voltage control in active distribution networks. IEEE Transactions on Power Systems, 33(2), 1374-1384.

Cai, J., Chen, C., Duan, S., & Yang, D. (2014). Centralized control of large capacity parallel connected power conditioning system for battery energy storage system in microgrid. In 2014 IEEE Energy Conversion Congress and Exposition (ECCE) (pp. 409-413).

Campbell, R. J. (2018). The smart grid: Status and outlook. Congressional Research Service, 7-5700.

Chathurangi, D., Jayatunga, U., Perera, S., Agalgaonkar, A., & Siyambalapitiya, T. (2021). Comparative evaluation of solar PV hosting capacity enhancement using Volt-VAr and Volt-Watt control strategies. Renewable Energy, 177, 1063-1075.

Chen, G., & Yang, Q. (2017). An ADMM-based distributed algorithm for economic dispatch in islanded microgrids. IEEE Transactions on Industrial Informatics, 14(9), 3892-3903.

Cozzi, L., Gould, T., Bouckart, S., Crow, D., Kim, T., Mcglade, C.,Wetzel, D. (2020). World Energy Outlook 2020. vol, 2050, 1-461.

Deng, W., Lai, M.-J., Peng, Z., & Yin, W. (2017). Parallel multi-block ADMM with O (1/k) convergence. Journal of Scientific Computing, 71(2), 712-736.

Gerdroodbari, Y. Z., Razzaghi, R., & Shahnia, F. (2021). Decentralized control strategy to improve fairness in active power curtailment of PV inverters in low-voltage distribution networks. IEEE Transactions on Sustainable Energy, 12(4), 2282-2292.

Ghosh, S., Rahman, S., & Pipattanasomporn, M. (2016). Distribution voltage regulation through active power curtailment with PV inverters and solar generation forecasts. IEEE Transactions on Sustainable Energy, 8(1), 13-22.

Grigsby, L. L. (2007). Power system stability and control. CRC press.

Guo, Y., Wu, Q., Gao, H., Huang, S., Zhou, B., & Li, C. (2019). Double-time-scale coordinated voltage control in active distribution networks based on MPC. IEEE Transactions on Sustainable Energy, 11(1), 294-303.

Gush, T., Kim, C.-H., Admasie, S., Kim, J.-S., & Song, J.-S. (2021). Optimal Smart Inverter Control for PV and BESS to Improve PV Hosting Capacity of Distribution Networks Using Slime Mould Algorithm. IEEE Access, 9, 52164-52176.

Han, Y., Ning, X., Yang, P., & Xu, L. (2019). Review of power sharing, voltage restoration and stabilization techniques in hierarchical controlled DC microgrids. IEEE Access, 7, 149202-149223.

He, C., Wu, L., Liu, T., & Shahidehpour, M. (2016). Robust co-optimization scheduling of electricity and natural gas systems via ADMM. IEEE Transactions on Sustainable Energy, 8(2), 658-670.

Hu, J., Marinelli, M., Coppo, M., Zecchino, A., & Bindner, H. W. (2016). Coordinated voltage control of a decoupled three-phase on-load tap changer transformer and photovoltaic inverters for managing unbalanced networks. Electric Power Systems Research, 131, 264-274.

Huang, S., Wu, Q., Guo, Y., Chen, X., Zhou, B., & Li, C. (2019). Distributed voltage control based on ADMM for large-scale wind farm cluster connected to VSC-HVDC. IEEE Transactions on Sustainable Energy, 11(2), 584-594.

IEA. (2020a). Renewable energy market update. Repéré à https://www.iea.org/reports/renewable-energy-market-update-may-2022.

IEA. (2020b). Tracking Energy Integration: Energy Storage. Repéré à https://www.iea.org/reports/ tracking-energy-integration.

Impram, S., Nese, S. V., & Oral, B. (2020). Challenges of renewable energy penetration on power system flexibility: A survey. Energy Strategy Reviews, 31, 100539.

IRENA (2017), Electricity Storage and Renewables: Costs and Markets to 2030, International Renewable Energy Agency, Abu Dhabi.

IRENA. (2019). Future of Solar Photovoltaic: Deployment, investment, technology, grid integration and socio-economic aspects (A Global Energy Transformation: paper). International Renewable Energy Agency, Abu Dhabi. Repéré à https://www.irena.org/publications/2019/Nov/Future-of-Solar-Photovoltaic

IRENA. (2022). Renewable capacity highlights 2022. Repéré à https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2022/Apr/IRENA_-RE_Capacity_Highlights_2022.pdf?la=en&hash=6122BF5666A36BECD5AAA2050B011ECE255B3BC7#:~:text=11%20April%202022&text=Renewable%20generation%20capacity%20increased%20by,10%20GW%20(%2B8%25).

Ishaq, S., Khan, I., Rahman, S., Hussain, T., Iqbal, A., & Elavarasan, R. M. (2022). A review on recent developments in control and optimization of micro grids. Energy Reports, 8, 4085-4103.

Kabir, M. N., Mishra, Y., Ledwich, G., Dong, Z. Y., & Wong, K. P. (2014). Coordinated control of grid-connected photovoltaic reactive power and battery energy storage systems to improve the voltage profile of a residential distribution feeder. IEEE Transactions on Industrial Informatics, 10(2), 967-977.

Kabirifar, M., Pourghaderi, N., Rajaei, A., Moeini-Aghtaie, M., & Safdarian, A. (2020). Deterministic and probabilistic models for energy management in distribution systems. In Handbook of Optimization in Electric Power Distribution Systems (pp. 343-382). Springer.

Kargarian, A., Mohammadi, J., Guo, J., Chakrabarti, S., Barati, M., Hug, G., . . . Baldick, R. (2016). Toward distributed/decentralized DC optimal power flow implementation in future electric power systems. IEEE Transactions on Smart Grid, 9(4), 2574-2594.

Keane, A., Ochoa, L. F., Vittal, E., Dent, C. J., & Harrison, G. P. (2010). Enhanced utilization of voltage control resources with distributed generation. IEEE Transactions on Power Systems, 26(1), 252-260.

Kou, X., Li, F., Dong, J., Starke, M., Munk, J., Xue, Y., . . . Zandi, H. (2020). A scalable and distributed algorithm for managing residential demand response programs using alternating direction method of multipliers (ADMM). IEEE Transactions on Smart Grid, 11(6), 4871-4882.

Kumar, D. S., Gandhi, O., Rodríguez-Gallegos, C. D., & Srinivasan, D. (2020). Review of power system impacts at high PV penetration Part II: Potential solutions and the way forward. Solar Energy, 210, 202-221.

Le Dinh, K., & Hayashi, Y. (2013). Coordinated BESS control for improving voltage stability of a PV-supplied microgrid. In 2013 48th International Universities' Power Engineering Conference (UPEC) (pp. 1-6). IEEE.

Lewis, F., Zhang, H., Hengster-Movric, K., & Das, A. (2014). Cooperative Control of Multi-Agent Systems, ser. Communications and Control Engineering: London: Springer London.

Li, M., Gao, J., Chen, N., Zhao, L., & Shen, X. (2019). Decentralized PEV power allocation with power distribution and transportation constraints. IEEE Journal on Selected Areas in Communications, 38(1), 229-243.

Li, P., Yang, M., Tang, Y., Yu, Y., & Li, M. (2021). Robust decentralized coordination of transmission and active distribution networks. IEEE Transactions on Industry Applications, 57(3), 1987-1994.

Li, W., Liu, Y., Liang, H., & Shen, Y. (2020). A new distributed energy management strategy for smart grid with stochastic wind power. IEEE Transactions on Industrial Electronics, 68(2), 1311-1321.

Liu, H. J., Shi, W., & Zhu, H. (2017). Distributed voltage control in distribution networks: Online and robust implementations. IEEE Transactions on Smart Grid, 9(6), 6106-6117.

Liu, Y., Guo, L., Lu, C., Chai, Y., Gao, S., & Xu, B. (2019). A fully distributed voltage optimization method for distribution networks considering integer constraints of step voltage regulators. IEEE Access, 7, 60055-60066.

Liu, Y., Li, Y., Gooi, H. B., Jian, Y., Xin, H., Jiang, X., & Pan, J. (2017). Distributed robust energy management of a multimicrogrid system in the real-time energy market. IEEE Transactions on Sustainable Energy, 10(1), 396-406.

Lofberg, J. (2004). YALMIP: A toolbox for modeling and optimization in MATLAB. In 2004 IEEE international conference on robotics and automation (IEEE Cat. No. 04CH37508) (pp. 284-289). IEEE.

Lu, L.-Y., & Chu, C.-C. (2017). Consensus-based droop control of isolated micro-grids by ADMM implementations. IEEE Transactions on Smart Grid, 9(5), 5101-5112.

Magnússon, S., Weeraddana, P. C., & Fischione, C. (2015). A distributed approach for the optimal power-flow problem based on ADMM and sequential convex approximations. IEEE Transactions on Control of Network Systems, 2(3), 238-253.

Mahmud, N., & Zahedi, A. (2016). Review of control strategies for voltage regulation of the smart distribution network with high penetration of renewable distributed generation. Renewable and Sustainable Energy Reviews, 64, 582-595.

Manshadi, S. D., Liu, G., Khodayar, M. E., Wang, J., & Dai, R. (2019). A distributed convex relaxation approach to solve the power flow problem. IEEE Systems Journal, 14(1), 803-812.

Mohammadjafari, M., Ebrahimi, R., & Parvin Darabad, V. (2020). Optimal energy management of a microgrid incorporating a novel efficient demand response and battery storage system. Journal of Electrical Engineering & Technology, 15(2), 571-590.

Mohammed, A. M., Alalwan, S. N. H., Taşcıkaraoğlu, A., & Catalão, J. P. (2022). Sliding mode-based control of an electric vehicle fast charging station in a DC microgrid. Sustainable Energy, Grids and Networks, 32, 100820.

Mohan, S., Hasan, S., Gebremariam, Y., & Varma, R. K. (2018). Increasing hosting capacity of pv solar systems using smart inverter volt-var control. In 2018 20th National Power Systems Conference (NPSC) (pp. 1-6). IEEE.

Mokhtari, G., Nourbakhsh, G., & Ghosh, A. (2013). Smart coordination of energy storage units (ESUs) for voltage and loading management in distribution networks. IEEE Transactions on Power Systems, 28(4), 4812-4820.

Molzahn, D. K., Dörfler, F., Sandberg, H., Low, S. H., Chakrabarti, S., Baldick, R., & Lavaei, J. (2017). A survey of distributed optimization and control algorithms for electric power systems. IEEE Transactions on Smart Grid, 8(6), 2941-2962.

Morstyn, T., Hredzak, B., & Agelidis, V. G. (2016). Control strategies for microgrids with distributed energy storage systems: An overview. IEEE Transactions on Smart Grid, 9(4), 3652-3666.

Nazir, M. S., Abdalla, A. N., Wang, Y., Chu, Z., Jie, J., Tian, P., . . . Tang, Y. (2020). Optimization configuration of energy storage capacity based on the microgrid reliable output power. Journal of Energy Storage, 32, 101866.

Nguyen, T.-L., Wang, Y., Tran, Q.-T., Caire, R., Xu, Y., & Gavriluta, C. (2020). A Distributed Hierarchical Control Framework in Islanded Microgrids and Its Agent-Based Design for Cyber–Physical Implementations. IEEE Transactions on Industrial Electronics, 68(10), 9685-9695.

Nijhuis, M., Gibescu, M., & Cobben, J. (2015). Assessment of the impacts of the renewable energy and ICT driven energy transition on distribution networks. Renewable and Sustainable Energy Reviews, 52, 1003-1014.

Nikmehr, N. (2020). Distributed robust operational optimization of networked microgrids embedded interconnected energy hubs. Energy, 199, 117440.

Olivella-Rosell, P., Rullan, F., Lloret-Gallego, P., Prieto-Araujo, E., Ferrer-San-José, R., Barja-Martinez, S., . . . Forsström, J. (2020). Centralised and distributed optimization for aggregated flexibility services provision. IEEE Transactions on Smart Grid, 11(4), 3257-3269.

Pearre, N., & Swan, L. (2020). Reimagining renewable electricity grid management with dispatchable generation to stabilize energy storage. Energy, 203, 117917.

Photovoltaics, D. G., & Storage, E. (2009). IEEE Application Guide for IEEE Std 1547™, IEEE Standard for Interconnecting Distributed Resources with Electric Power Systems.

Photovoltaics, D. G., & Storage, E. (2018). IEEE standard for interconnection and interoperability of distributed energy resources with associated electric power systems interfaces. IEEE Std, 1547-2018.

Rafi, F., Hossain, M., & Lu, J. (2016). Hierarchical controls selection based on PV penetrations for voltage rise mitigation in a LV distribution network. International Journal of Electrical Power & Energy Systems, 81, 123-139.

Rajaei, A., Fattaheian-Dehkordi, S., Fotuhi-Firuzabad, M., Moeini-Aghtaie, M., & Lehtonen, M. (2021). Developing a distributed robust energy management framework for active distribution systems. IEEE Transactions on Sustainable Energy, 12(4), 1891-1902.

Ranaweera, I., Midtgård, O.-M., & Korpås, M. (2017). Distributed control scheme for residential battery energy storage units coupled with PV systems. Renewable Energy, 113, 1099-1110.

Ravindra, H., Faruque, M. O., Schoder, K., Steurer, M., Mclaren, P., & Meeker, R. (2012). Dynamic interactions between distribution network voltage regulators for large and distributed PV plants. In PES T&D 2012 (pp. 1-8). IEEE.

Safavizadeh, A., Yousefi, G. R., & Karshenas, H. R. (2017). Voltage variation mitigation using reactive power management of distributed energy resources in a smart distribution system. IEEE Transactions on Smart Grid, 10(2), 1907-1915.

Sallam, A. A., & Malik, O. P. (2018). Electric distribution systems.

Shi, D., & Sharma, R. K. (2013). Adaptive control of energy storage for voltage regulation in distribution system. In 2013 IEEE International Conference on Smart Energy Grid Engineering (SEGE) (pp. 1-7). IEEE.

Shuai, Z., Fang, J., Ning, F., & Shen, Z. J. (2018). Hierarchical structure and bus voltage control of DC microgrid. Renewable and Sustainable Energy Reviews, 82, 3670-3682.

Sun, H., Guo, Q., Qi, J., Ajjarapu, V., Bravo, R., Chow, J., . . . Tamrakar, U. (2019). Review of challenges and research opportunities for voltage control in smart grids. IEEE Transactions on Power Systems, 34(4), 2790-2801.

Suresh, A. (2021). Novel Approaches in Modeling Integrated Power Transmission and Distribution System with Distributed Energy Resources and Controls (The University of North Carolina at Charlotte).

Tahir, M. (2019). Coordinated Voltage and Reactive Power Control for Renewable Dominant Smart Distribution Systems.

Tewari, T., Mohapatra, A., & Anand, S. (2020). Coordinated control of OLTC and energy storage for voltage regulation in distribution network with high PV penetration. IEEE Transactions on Sustainable Energy, 12(1), 262-272.

Tian, P., Xiao, X., Wang, K., & Ding, R. (2015). A hierarchical energy management system based on hierarchical optimization for microgrid community economic operation. IEEE Transactions on Smart Grid, 7(5), 2230-2241.

Tonkoski, R., Turcotte, D., & El-Fouly, T. H. (2012). Impact of high PV penetration on voltage profiles in residential neighborhoods. IEEE Transactions on Sustainable Energy, 3(3), 518-527.

Tuominen, J., Repo, S., & Kulmala, A. (2014). Comparison of the low voltage distribution network voltage control schemes. In IEEE PES Innovative Smart Grid Technologies, Europe (pp. 1-6). IEEE.

Unigwe, O. C. (2020). Coordination of distributed battery energy storage systems in networks with high penetration of photovoltaics.

Varma, R. K. (2021). Smart solar PV inverters with advanced grid support functionalities. John Wiley & Sons.

Von Appen, J., Stetz, T., Braun, M., & Schmiegel, A. (2014). Local voltage control strategies for PV storage systems in distribution grids. IEEE Transactions on Smart Grid, 5(2), 1002-1009.

Vovos, P. N., Kiprakis, A. E., Wallace, A. R., & Harrison, G. P. (2007). Centralized and distributed voltage control: Impact on distributed generation penetration. IEEE Transactions on Power Systems, 22(1), 476-483.

Wang, L., Bai, F., Yan, R., & Saha, T. K. (2018). Real-time coordinated voltage control of PV inverters and energy storage for weak networks with high PV penetration. IEEE Transactions on Power Systems, 33(3), 3383-3395.

Wang, L., Liang, D. H., Crossland, A. F., Taylor, P. C., Jones, D., & Wade, N. S. (2015). Coordination of multiple energy storage units in a low-voltage distribution network. IEEE Transactions on Smart Grid, 6(6), 2906-2918.

Wang, L., Yuan, M., Zhang, F., Wang, X., Ma, J., Dai, L., . . . Bi, R. (2020). Research on large-scale photovoltaic planning based on risk assessment in distribution network. Journal of Electrical Engineering & Technology, 15(3), 1107-1114.

Wang, M., Su, Y., Chen, L., Li, Z., & Mei, S. (2019). Distributed optimal power flow of DC microgrids: A penalty based ADMM approach. CSEE Journal of Power and Energy Systems, 7(2), 339-347.

Wang, X., Wang, C., Xu, T., Guo, L., Li, P., Yu, L., & Meng, H. (2018). Optimal voltage regulation for distribution networks with multi-microgrids. Applied energy, 210, 1027-1036.

Wang, X., Wang, C., Xu, T., Meng, H., Li, P., & Yu, L. (2018). Distributed voltage control for active distribution networks based on distribution phasor measurement units. Applied energy, 229, 804-813.

Wang, X., Yan, J., Jin, B., & Li, W. (2019). Distributed and parallel ADMM for structured nonconvex optimization problem. IEEE transactions on cybernetics, 51(9), 4540-4552.

Wang, Y., Syed, M. H., Guillo-Sansano, E., Xu, Y., & Burt, G. M. (2019). Inverter-based voltage control of distribution networks: A three-level coordinated method and power hardware-in-the-loop validation. IEEE Transactions on Sustainable Energy, 11(4), 2380-2391.

Wang, Y., Xu, Y., Tang, Y., Liao, K., Syed, M. H., Guillo-Sansano, E., & Burt, G. M. (2018). Aggregated energy storage for power system frequency control: A finite-time consensus approach. IEEE Transactions on Smart Grid, 10(4), 3675-3686.

Wang, Y., Zhang, P., Li, W., Xiao, W., & Abdollahi, A. (2012). Online overvoltage prevention control of photovoltaic generators in microgrids. IEEE Transactions on Smart Grid, 3(4), 2071-2078.

Weedy, B. M., Cory, B. J., Jenkins, N., Ekanayake, J. B., & Strbac, G. (2012). Electric power systems. John Wiley & Sons.

Xu, Q., Xiao, J., Wang, P., Pan, X., & Wen, C. (2017). A decentralized control strategy for autonomous transient power sharing and state-of-charge recovery in hybrid energy storage systems. IEEE Transactions on Sustainable Energy, 8(4), 1443-1452.

Xu, S., Xue, Y., & Chang, L. (2021). Review of power system support functions for inverter-based distributed energy resources-standards, control algorithms, and trends. IEEE open journal of Power electronics, 2, 88-105.

Zeng, Y., Zhang, Q., Liu, Y., Zhuang, X., & Guo, H. (2021). Hierarchical Cooperative Control Strategy for Battery Storage System in Islanded DC Microgrid. IEEE Transactions on Power Systems.

Zeraati, M., Golshan, M. E. H., & Guerrero, J. M. (2016). Distributed control of battery energy storage systems for voltage regulation in distribution networks with high PV penetration. IEEE Transactions on Smart Grid, 9(4), 3582-3593.

Zeraati, M., Golshan, M. E. H., & Guerrero, J. M. (2017). A consensus-based cooperative control of PEV battery and PV active power curtailment for voltage regulation in distribution networks. IEEE Transactions on Smart Grid, 10(1), 670-680.

Zhang, Y., Meng, K., Luo, F., Yang, H., Zhu, J., & Dong, Z. Y. (2019). Multi-agent-based voltage regulation scheme for high photovoltaic penetrated active distribution networks using battery energy storage systems. IEEE Access, 8, 7323-7333.

Zhao, P., Dou, C., Ma, K., Zhang, Z., & Zhang, B. (2020). Distributed cooperative control based on multiagent system for islanded microgrids with switching topology and channel interruption. IEEE Systems Journal.

Zhao, T., & Ding, Z. (2017). Distributed agent consensus-based optimal resource management for microgrids. IEEE Transactions on Sustainable Energy, 9(1), 443-452.

Zheng, W., Wu, W., Zhang, B., Sun, H., & Liu, Y. (2015). A fully distributed reactive power optimization and control method for active distribution networks. IEEE Transactions on Smart Grid, 7(2), 1021-1033.

Zhong, W., Xie, K., Liu, Y., Yang, C., Xie, S., & Zhang, Y. (2019). Admm empowered distributed computational intelligence for Internet of energy. IEEE Computational Intelligence Magazine, 14(4), 42-51.

Zimmerman, R., & Murillo-Sanchez, C. (2019). Matpower (version 7.1) [software]. Zenodo. Available online: https://zenodo. org/record/4074135#. Yc6JdlkRWNI (accessed on 15 October 2021).