OPTIMAL POWER CONTROL OF GRID-CONNECTED DISTRIBUTED GENERATION IN A HIERARCHICAL FRAMEWORK BASED ON MODEL PREDICTIVE CONTROL

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ABSTRACT

Ph.D. Thesis

OPTIMAL POWER CONTROL OF GRID-CONNECTED DISTRIBUTED GENERATION IN A HIERARCHICAL FRAMEWORK BASED ON MODEL PREDICTIVE CONTROL

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In the modern era, managing optimal real-time control of microgrids during the operational phase has been a significant challenge, requiring careful consideration of both technical and economic factors. This thesis introduces a framework for the real-time control of islanded and grid-connected microgrids using a preserving network. This structure incorporates various distributed generation sources, including rotating and non-rotating resources and energy storage systems. The optimization function within model predictive control (MPC) manages essential network parameters like frequency and voltage while addressing real-time economic and technical objectives. To enhance precision and account for uncertainties in generation and consumption parameters, the integration of continuous power flow and the preserving network model is employed. This approach aims to create a model that closely mirrors real-world conditions, ensuring a more accurate representation of microgrid dynamics. The proposed structure demonstrates significant improvements in both technical and economic performance compared to standard MPC and adaptive MPC, highlighting its potential for more efficient islanded and grid-connected microgrid management. In islanded mode, the proposed framework achieves notable reductions in total voltage deviation of 85.87% and 87.62% compared to Standard MPC and Adaptive MPC, respectively. Economically, the proposed framework significantly outperforms both, reducing costs by 39.29% compared to Standard MPC and by 28.12% compared to Adaptive MPC. In grid-connected mode, the proposed framework achieves significant reductions in total voltage deviation of 37.5% compared to Adaptive MPC and 73.68% compared to Standard MPC. Economically, the proposed framework also outperforms both, reducing costs by 24.19% compared to Standard MPC and by 35.83% compared to Adaptive MPC.

Keyword : Model predictive control, Distributed generation, Hierarchical controller, Hybrid microgrid

Science Code : 93402

ÖZET

Doktora Tezi

MODEL ÖNGÖRÜLÜ KONTROLE DAYALI HİYERARŞİK BİR ÇERÇEVEDE ŞEBEKEYE BAĞLI DAĞITILMIŞ ÜRETİMİN OPTİMUM GÜÇ KONTROLÜ

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In the modern era, managing optimal real-time control of microgrids during the Modern çağda, işletme aşamasında mikro şebekelerin optimum gerçek zamanlı kontrolünü yönetmek, hem teknik hem de ekonomik faktörlerin dikkatli bir şekilde değerlendirilmesini gerektiren önemli bir zorluk olmuştur. Bu tez, bir koruma ağı kullanarak adalı ve şebekeye bağlı mikro şebekelerin gerçek zamanlı kontrolü için bir çerçeve sunmaktadır. Bu yapı, dönen ve dönmeyen kaynaklar ve enerji depolama sistemleri dahil olmak üzere çeşitli dağıtılmış üretim kaynaklarını içermektedir. Model öngörülü kontrol (MPC) içindeki optimizasyon işlevi, gerçek zamanlı ekonomik ve teknik hedefleri ele alırken frekans ve voltaj gibi temel ağ parametrelerini yönetir. Hassasiyeti artırmak ve üretim ve tüketim parametrelerindeki belirsizlikleri hesaba katmak için, sürekli güç akışı ve koruyucu şebeke modelinin entegrasyonu kullanılır. Bu yaklaşım, mikro şebeke dinamiklerinin daha doğru bir şekilde temsil edilmesini sağlayarak gerçek dünya koşullarını yakından yansıtan bir model oluşturmayı amaçlamaktadır. Önerilen yapı, standart MPC ve uyarlanabilir MPC'ye kıyasla hem teknik hem de ekonomik performansta önemli gelişmeler göstererek daha verimli adalı ve şebekeye bağlı mikro şebeke yönetimi için potansiyelini vurgulamaktadır. Adalı modda, önerilen çerçeve Standart MPC ve Uyarlanabilir MPC'ye kıyasla toplam gerilim sapmasında sırasıyla %85,87 ve %87,62'lik kayda değer düşüşler elde etmektedir. Ekonomik olarak, önerilen çerçeve her ikisinden de önemli ölçüde daha iyi performans göstererek maliyetleri Standart MPC'ye kıyasla %39,29 ve Uyarlamalı MPC'ye kıyasla %28,12 oranında azaltmaktadır. Şebekeye bağlı modda, önerilen çerçeve toplam gerilim sapmasında Adaptif MPC'ye kıyasla %37,5 ve Standart MPC'ye kıyasla %73,68 oranında önemli düşüşler sağlamaktadır. Ekonomik açıdan da önerilen çerçeve, maliyetleri Standart MPC'ye kıyasla %24,19 ve Uyarlamalı MPC'ye kıyasla %35,83 oranında azaltarak her ikisinden de daha iyi performans göstermektedir.

Anahtar Sözcükler : Model öngörülü kontrol, Dağıtık üretim, Hiyerarşik kontrolör, Hibrit mikroşebeke

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ABBREVITIONS

PNLMPC	: Proposed Nonlinear Model Predictive Control
NLMPC	: Nonlinear Model Predictive Control
MPC	: Model Predictive Control
PDF	: Probability Distribution Function
CPF	: Continuous Power Flow
NPM	: Network Preserving Model
BESS	: Battery Energy Storage System
DER	: Distributed Energy Resources
DG	: Distributed Generators
MG	: Microgrid
RES	: Renewable Energy Sources

PART 1

INTRODUCTION

This chapter describes an overview of microgrids (MGs) and their evolution as the core component in next-generation power systems. The chapter explains how MGs emerged as a response to the growing demand for clean, resilient, and decentralized energy supply. The chapter describes the fundamental modes of MG operation (grid-connected and islanded) and introduces a detailed classification based on structural configuration, including AC, DC, and hybrid systems. Additionally, it examines the major technical and operational challenges associated with integrating MGs into the main utility grid, such as interoperability, stability, protection coordination, and control complexity.

1.1. BACKGROUND

Microgrids (MGs) can be classified based on their structural configuration and operational mode. Structurally, MGS are typically divided into three types: AC MGs, DC MGs, and hybrid AC/DC MGs [1]. Functionally, MGs can be categorized as either grid-connected, island, or in a transitional phase between these states [2]. In grid-connected mode, the voltage and frequency support are provided by the main grid, and the DGs are primarily required to generate power. However, frequency control in islanded MGs poses significant challenges due to their reliance on non-inertial sources interconnected by power electronics converters [3]. Control of the frequency in MG through the use of virtual inertia, which employs features of model predictive control (MPC) [4].

While the connection to the national grid is not feasible, islanded MGs are typically deployed in a more remote location. In this mode, the DG systems are responsible for the control of voltage and frequency. Nevertheless, this type of design often incorporates energy storage solutions such as batteries and supercapacitors, which buffer fluctuations in energy supply and demand caused by the geographical distribution of energy sources and the inherent unpredictability of the system [5]. In such isolated and variable environments, effective energy management becomes essential [6].

Given that many RESs, such as photovoltaic arrays, fuel cells, and batteries, produce direct current, and electronic and control equipment, including induction motor drives, computers, and telecommunication equipment, require DC voltage to operate, researchers suggest the use of DC MGs to improve system efficiency [7-9]. The advantages of DC MGs, such as the absence of resource synchronization requirements, lower losses than AC systems, lack of reactive power and skin effect, increased transmission line capacity, and simpler control compared to AC systems, make them an attractive option for researchers.

Despite the advantages of DC MGs, it is not economically viable to change the nature of the existing networks due to the structures created in the distribution network and the spread of electrical appliances whose input is AC. Therefore, researchers in this field prioritize the optimal control of AC MGs. Research in this area is being conducted in energy management [10-12], power quality [13, 14], the structure of interfacing converters [15, 16], etc.

DGs are directly connected to the grid in AC MGs, such as diesel generators. In contrast, other DGs are connected to the grid with a power electronic interface converter like photovoltaic and fuel cells. The presence of DGs with an interface converter has advantages and disadvantages in a MG. One of the disadvantages of using DGs with interface converters is that they do not have inertia [17], which affects the stability margin of the MG. Virtual inertia can be created to some extent by using MPC [18]. Among their advantages, it can be mentioned that when their extra capacity is used in the converter, these converters can improve power quality indicators such as harmonic reduction, reactive power injection, etc. [13, 18].

Hybrid AC-DC MGs effectively and efficiently utilize DGs and AC and DC loads. Hybrid MGs consist of two sub-grids, AC and DC, and an interlinking converter (IC) that connects these two sub-grids [19, 20]. Hybrid MGs have the advantages of both types of AC and DC MGs. Due to the reduction of the number of layers of electronic power converters in these MGs and the reduction of losses, the efficiency of these MGs increases. At the same time, their control and operation are much more complicated than AC and DC MGs. Also, this complexity will be doubled if energy storage sources are added to the MG (which is unavoidable) [21]. Considering the advantages of these MGs, hybrid MGs can be considered future MGs [22, 23].

1.2. GENERAL PROBLEM STATEMENT

Modern MGs play a vital role in integrating Distributed Energy Resources (DERs) into power networks [24]. These MGs, composed of RES such as photovoltaics, wind turbines, and fuel cells, face significant challenges related to the control of active and reactive power. The management of these distributed generation (DG) units becomes complex due to the intermittent and uncertain nature of RES. Moreover, the incorporation of converter-based DGs in MGs introduces difficulties such as lack of inertia, grid stability issues, and operational inefficiencies [25, 26].

Despite the increasing interest in improving the control mechanisms for DGs in MGs, many existing studies focus solely on specific technical [27] or economic parameters [28, 29] without fully integrating the two aspects. In particular, the control of active and reactive power is often overlooked, which can lead to inefficient power management and higher operating costs. Furthermore, hierarchical control structures and MPC techniques, which offer the potential to optimize both technical performance and economic objectives, have not been sufficiently explored, especially in the context of hybrid AC/DC MGs. Thus, the problem arises from the lack of comprehensive and integrated control frameworks that can simultaneously manage active and reactive power in DGs while balancing economic feasibility and technical stability in MGs. Additionally, the hybrid AC/DC MG, while offering advantages such as reduced losses and increased system efficiency, presents control and operational challenges, particularly when energy storage systems are involved.

The proposed solution is a hierarchical control framework based on MPC, which will address the simultaneous and online control of active and reactive power in DGs, improve technical parameters (such as voltage stability, frequency, and losses), and reduce the operating costs of MGs. This approach is validated through simulation and comparison with previous methods using MATLAB.

1.3. CURRENT GAP IN THE AREA OF STUDY

In recent years, advancements have been achieved in the development of MG control systems, especially in the use of MPC. However, there are still several important outstanding research challenges that prevent the optimization and efficient utilization of DG resources for MGs. These challenges consist of the limited focus on the economic and technical control objectives, the absence of hierarchical control strategies, difficulties in managing active and reactive power, and the underutilization of hybrid AC/DC MGs.

1.3.1. Novelties of Current Study

This research proposes several important advancements in existing MG management technologies in terms of control mechanisms and the implementation of DG in power systems. The framework of management control in current research incorporates real-time adjustment and sophisticated improvement to explain why this study intends to develop further the management of MGs beyond what has already been done. The following novelties are highlighted as critical contributions of the study.

1. **Hierarchical Framework Utilizing MPC:** This study proposes a novel hierarchical control framework based on MPC that simultaneously addresses the active and reactive power control of grid-connected DGs while considering both technical and economic objectives. This dual focus aims to optimize the performance of MGs comprehensively.
2. **Real-Time Control of Power Generation:** The proposed method includes real-time adjustments of DG output in response to changing weather and

ambient conditions (e.g., irradiance and wind speed). This adaptability enhances the reliability and efficiency of power generation in MGs.

3. **Enhanced Technical Parameters:** The study aims to improve critical technical parameters of the network, such as voltage stability, frequency control, and loss minimization, thereby addressing significant challenges identified in previous research.
4. **User-Friendly Interface for Implementation:** The proposal emphasizes the development of a user-friendly interface to facilitate the implementation of hierarchical control in MGs, enhancing usability for operators and stakeholders.
5. **Incorporation of Energy Storage Control:** The research integrates the control of charge and discharge cycles of energy storage devices within the hierarchical structure, providing a comprehensive approach to energy management in AC/DC hybrid MGs. This aspect is critical for compensating fluctuations and ensuring stability.

By addressing these gaps and introducing these novelties, this study aims to advance the field of MG control and contribute significantly to the effective integration of DGs within power networks.

1.4. PURPOSED AND OBJECTIVES OF RESEARCH

The main purpose of this thesis is to design and implement an intelligent hierarchical MPC framework that addresses both the technical and economic aspects of MG. The objectives of the proposed strategy is structured around three major areas: uncertainty management, economic optimization, and technical improvement, explained below:

1. **Managing Uncertainties**
   - Ensure optimal control of active and reactive power from DGs under dynamic environmental conditions like irradiance and wind speed.
2. **Economic Optimization**
   - Minimize operation costs related to generation and energy storage systems.

3. **Technical Enhancement**
    - Enhance technical performance by providing frequency stability, voltage stability.
    - Enable dynamic energy storage management in hybrid AC/DC MGs using optimal charge/discharge controls.

By integrating these objectives into a centralized hierarchical MPC structure, the system enables smart, adaptive, and cost-effective control of MGs, thus assuring both reliability and economic optimization, thus assuring both reliability and economic efficiency.

1.5. SCOPE AND LIMITATIONS OF THE CURRENT STUDY

This section describes the scope and limitations of this research, clearly distinguishing between what the study endeavours to investigate and any factors that may limit the research outcome.

1. **Hierarchical Control Framework:** The study will focus on developing a robust hierarchical control framework that integrates various levels of control (processing, sensing, monitoring, and maintenance) to efficiently manage active and reactive power in MGs.
2. **Application of MPC:** The research will implement MPC techniques to optimize the operation of grid-connected DGs, thereby addressing the challenges posed by fluctuating RES and ensuring reliable power supply.
3. **Hybrid AC/DC MGs:** The study will specifically explore the implementation of the proposed control strategies within hybrid AC/DC MGs, assessing their performance compared to traditional AC MGs.
4. **Validation through Simulation:** The effectiveness of the proposed control methods will be validated through simulations conducted in MATLAB, with comparisons drawn against existing control methodologies in recent literature.

1.6. THESIS ORGANIZATION

This thesis is organized into several distinct sections that unfold progressively. Chapter Two contains a comprehensive literature review that underpins the research in question. The third chapter details the problem formulation and the methodologies in order to give a clear picture of the research design. Chapter Four, the culmination of this research, is presented, intertwining results and discussions to reveal valuable insights. Lastly, Chapter Five provides a summary of the whole undertaking, presenting major recommendations and the conclusions drawn.

PART 2

LITERATURE REVIEW

In this chapter, various methods for integrating DERs, including RESs and energy storage systems (ESSs), are investigated. This review covers the different strategies in this context, with a particular focus on the application of MPC in the integration of MGs into the main grid.

2.1. INTRODUCTION

The majority of DERs, which include DGs and RESs, are used in small electrical power grids known as MGs [30-34]. Functionally, MGs can be categorized as either grid-connected, islanded, or in transition between these two states [2, 35, 36]. Functionally, MGs can be categorized as either grid-connected, islanded, or in transition between these two states [2, 35, 36]. MPC has received significant attention in power systems engineering, particularly in MG energy management. Several factors contribute to this interest. Firstly, MPC is well-suited for systems heavily reliant on demand and renewable energy generation forecasts, as it is based on predictions of future system behavior [37]. Secondly, the system becomes more resilient to uncertainty, as MPC provides a feedback mechanism that allows for real-time adjustments to be made [38]. Lastly, MPC effectively manages power system constraints, including generator capacity and load balance, in the tertiary control layer [39].

Numerous studies have explored the use of MPC for effective power system management. The economic model predictive control (EMPC) approach has gained prominence as an effective solution for optimizing economic dispatch and integrating various energy storage systems [40, 41]. However, authors in reference [40] does not consider stochastic scenarios in handling wind power uncertainty and is oblivious to market dynamics and fluctuation in pricing. Similarly, Brahmia et al does not deal with the issues of applying various models to predict load demand and renewable energy generation [41]. While Li et al. have suggested a real-time multi-objective load dispatch strategy for biomass heat and power cogeneration using MPC [42]. While this paper gives a workable method to achieve real-time control, it overlooks operational reliability and transition times inherent in plants that convert biomass. The fact that the research does not consider independent variables that could have an impact on the performance of the proposed load dispatch control method, in view of external influences such as market dynamics or state policy changes, is overlooked. Furthermore, in reference [43], a distributed EMPC approach based on imprecise dual minimization is explored to tackle real-time economic dispatch problems. It is noteworthy, however, that the case study in this reference does not incorporate renewable generators and battery storage devices.

In this respect, Silva et al. have proposed an optimization scheme for a hybrid MPC approach that incorporates weather prediction using the weather research and forecasting (WRF) model. New rules in this setting have been introduced to deal with special needs of connection and disconnection, like minimum connection times and maximum connection frequencies. While the proposed model has been validated through simulations using real weather data, it has not yet been applied to any real MG. Additionally, the computational costs for this framework are high, and no provisions have been made for future policy changes related to grid connection [44]. In [45] , an approach is presented for integrating wind power into system operation in real-time using an MPC scheme, which addresses uncertainty and optimizes economic dispatch. Although it manages uncertainties in wind power, it does not sufficiently account for additional uncertainties arising from demand response programs due to the unpredictable behavior of customers. Rawlings et al propose a two-layer hierarchical approach using MPC to gain better cost savings and energy efficiency for large commercial HVAC systems. The research emphasizes the challenges of real-time control for both cost and economic dispatch problems. While this work introduces hierarchical decomposition for MPC, its evaluation is done mostly based on sample optimizations and simulation results and is lacking in terms of wide validation in the real world [46]. As emphasized by Pereira et al, NLMPC emerges as a promising approach for real-time MG control, providing a specialized solution to navigate the intricate and dynamic characteristics of DERs. While NLMPC can effectively address multiple control objectives, enhancing overall MG operation, it's important to note that this research focuses explicitly on controlling individual MGs rather than interconnected systems. Therefore, the NPM wasn't considered in this study [47].

Moreover, the performance of MG can be improved by using artificial intelligence (AI), and MPC. As Reference [48] introduces a data-driven NLMPC framework tailored for MG control. This framework adeptly captures the intricate and dynamic behavior of DERs through a data-driven approach leveraging sparse regression (SR). It's worth noting that the accuracy of this data-driven model hinges on the quality and quantity of available data used to train the SR model. While the framework demonstrates robust performance under realistic load patterns, underscoring its relevance for practical MG applications, it's important to acknowledge that it does not incorporate the NPM. As noted in [49], NLMPC demonstrates its capability to efficiently manage optimal energy distribution within interconnected multi-node MGs equipped with energy storage. By creating a virtual pool of distributed energy storage, NLMPC optimizes energy allocation and minimizes wear on storage devices. Additionally, the controller adeptly navigates diverse scenarios, including fluctuating weather conditions, varying load demands, and changing storage levels. However, it's important to note that the NPM does not directly apply in this specific context.

2.2. GENERAL BACKGROUND OF POWER SYSTEM

A power system can be defined as a set of electrical devices organized to create, transmit and distribute electrical energy to the end users [50]. This is done to provide electrical energy uninterruptedly to those who use it for household, commercial, and industrial purposes. Power systems include three main components: generation, transmission, and distribution [51, 52]. Electricity can be generated from different sources, such as conventional fuels, like coal, oil, or gas, nuclear power plants, and green energy sources, such as solar, wind, hydro, geothermal, and biowastes [53, 54]. Power plants may be either centralized large-scale plants or decentralized rooftops and other power generation facilities [55, 56].

To minimize power losses, the electricity produced at the power plant is transmitted over long distances from the power stations through high-tension power lines [57]. In power systems, transfer and distribution systems are typically distinguished between bulk power transmission, which involves long-distance transmission (e.g., hundreds or even thousands of kilometres), and local transmission mainly focusing on distribution to consumers [58, 59]. In these systems, substations are very important, as they use a set of transformers that increase transmission voltage and reduce it for distribution purposes. Electricity distribution proceeds from the substations to the consumers and consists of medium voltage and low voltage lines. Modern distribution systems frequently use smart grids, which means that they control and transmit information about the flow of electricity via a digital network. In order to keep the system stable, power systems are designed in a way that supply and demand are balanced throughout operations. For this matter, load forecasting and management techniques are employed to ensure that generation matches consumption. Engineers carefully study the power flow in the system to understand how the electricity is moving through the whole system, where the limitations are, and how to enhance the efficiency [60-62].

Nonetheless, electricity networks are subject to various issues, such as the existing ones disintegrating due to old age, leading to a wasteful and costly maintenance structure. The integration of RESs brings variability and uncertainty, which call for sophisticated management and storage systems. Moreover, conventional power generation methods contribute to carbon emissions, and therefore, switching to a source of energy that does not pollute the environment is a major challenge [63].

Power systems are evolving towards decentralization, with an increasing emphasis on decentralized generation (e.g., MGs), which is on the rise in consumer markets to enhance energy resilience. Advancements in energy storage technology, such as batteries, are becoming important for controlling intermittent RESs and providing backup power. The growth of electric vehicles (EVs) is changing the load patterns and will have considerable effects on the design and operation of power systems [55, 64-66].

2.3. IMPACT OF MICROGRIDS ON POWER SYSTEMS

MGs improve the reliability and resilience of electricity supply by supplying backup energy during grid outages. MGs mitigate the effects of disturbances on the main grid, resulting in a more stable electricity supply for local customers [65]. This capacity is especially important in locations susceptible to natural disasters or poor grid infrastructure. Furthermore, MGs make it easier to incorporate RESs like wind and solar into the energy mix. This integration reduces reliance on dependence upon fossil fuels and significantly cuts carbon emissions for environmental cleanliness. MGs are vital to advancing sustainable energy practices since they utilize locally available renewable resources. Another key benefit that MGs present is energy generation and consumption at a local level. Energy sources stand nearest to the point of consumption. This benefit reduces losses on transmission and hence guarantees effective management of energy supply in response to specific local demands. This local orientation ensures not only efficiency but also improves the entire energy structure [65, 67, 68].

Economically, MGs can bring in a lot of cost savings. MGs make it possible to profit from selling extra energy back to the grid by reducing power losses and electricity pricing. This financial flexibility can be of great help to communities that are seeking to enhance energy expendability. Communities gain control over their energy resources thanks to MGs. This leads to energy independence and enhances resilience in price fluctuations and supply disruptions. MGs not only provide strength to the local communities but also strengthen overall energy security [69-72].

2.3.1. Classification of Microgrids

MGs are divided into three main categories including: hybrid MGs, DC MGs, and AC MGs [22]. Each category has unique properties and uses in power distribution.

1. AC MGs utilize alternating current for power distribution. These are usually easier to integrate with the existing grid infrastructure. They can support

various RESs and find applications in residential, commercial, and industrial sectors [73, 74].

2. DC MGs run on direct current. They are suitable for applications where RESs, such as solar panels and energy storage devices like batteries, are available. They are effective for certain loads where DC loads are predominant, including data canters and electric vehicle charging stations [75, 76].
3. Hybrid MGs incorporate both AC and DC components, thus allowing much higher flexibility and optimization of energy management. Hybrid MGs can combine renewable sources, energy storage, and traditional generation to balance supply and demand between different loads [22, 77, 78].

2.3.2. Configuration of Microgrids

This section discusses two main forms of MGs, including grid-connected and islanded modes. each of these configurations has unique advantages and operational traits in relation to power systems [79, 80]. Each will be explained separately in the following.

1. Grid-Connected Mode: While in grid-connected mode, MGs are integrated with the main power grid. This configuration makes it possible to both import and export electricity, whereby the MG might require electricity during high consumption periods and, at the same time, during low consumption periods, return power to the grid. This mode improves the overall system operators' control and flexibility of the power system and also optimizes the use of RESs [81, 82].
2. Islanded Mode: In the islanded mode, MGs function without the interconnection of the main grid. This arrangement is advantageous in case of grid disconnections as the MG can still supply power to the local users. In this regard, islanded MGs can have local generation sources such as solar panels, wind turbines, and energy storage systems to provide a stable energy supply to the community [83, 84].

2.4. TYPES OF BUSES IN POWER SYSTEMS AND MICROGRIDS: ROLES AND FUNCTIONS

In power systems and MGs, buses are among the pivotal features that act as junctions for various electrical connections, thus enabling the interconnection of generators, loads, and other network elements. The various types of buses existing in the engineering field are generally classified by their respective activities as well as parameters controlled or observed at such points. The following are the major classifications of buses found in both conventional power systems and MGs [36, 85, 86]:

1. **Slack Bus (Swing Bus)**

Power System: The slack bus maintains a balance between the active and reactive power in large power systems. This bus modifies its generation to keep a steady system voltage and frequency in order to make up for power losses and imbalances [87].

MGs: The slack bus in MGs is known as the V/F bus. This bus plays a similar role, particularly when the MG operates in an islanded mode. It modifies its output to maintain voltage and frequency [88].

2. **PV Bus (Voltage-Controlled Bus)**

Power System: The active power and voltage magnitude are controlled by the PV bus (Power and Voltage bus). Generators connected to the PV bus control the output to maintain a constant voltage, whereas the reactive power can fluctuate to balance the load [89].

MGs: The concept of a PV bus in MGs mainly refers to the point of connection for RESs, like photovoltaic systems or wind turbines. These sources manage the output of active power, maintain a desired voltage, and change the reactive power as needed [90].

3. PQ Bus (Load Bus)

Power System: PQ buses are load buses, where the active and reactive power are specified and voltage is not regulated. The system's goal is to feed the voltage required to meet the load demand at these points due to these buses consuming power [91].

MGs: The PQ buses in MGs usually represent the loads, including household appliances, industrial equipment, and electric vehicle charging stations. These buses rely on MG's generation and storage for their active and reactive power demands [92].

2.5. NETWORK-PRESERVING MODEL

The Network-Preserving Model (NPM) is a type of power system model mainly used to represent electrical networks in dynamic simulations and stability analyses. Unlike Models that simplify the electrical network, such as the classical machine model or reduced network models, the network-preserving model retains a detailed structure of an electrical network with all of its buses, branches, and loads. This model is useful, particularly in analysing the dynamic behaviour of complex power systems and MGs, where precise representation of the network topology and interconnections is essential [93-96]. Here are the key features of NPMs:

1. **Complete network representation:** The model maintains the actual structure of the power system, comprising all transmission lines, transformers, generators, loads, and buses. Since every bus's voltage and frequency characteristics are precisely represented, it can be used in detailed simulations [97].
2. **Dynamic behavior:** The model can simulate transient and dynamic behavior of power systems as a result of disturbances, such as faults, switching events, or changes in load. This includes modelling how voltage and frequency vary across different parts of the network [98].
3. **Detailed Power Flow Equations: Unlike** the simplified models, the NPM utilizes full power flow equations to represent the transfer of active and reactive

power through the network. Thus, it gives more accurate results for stability and transient analysis [99].

4. **Generator Modelling**: The generators in the NPM are represented by detailed models, for example, by the swing equation or multi-state dynamic models. These comprise the internal states of the generator and how it interacts with the network, such as voltage and rotor angle dynamics [100].
5. **AC Power Flow:** The model uses AC **power** flow equations, which consider active and reactive power flows. Consequently, the model has been more adequate for voltage stability and reactive power support analysis in the grid [101].
6. **Preservation of network constraints:** The **model** has a detailed network layout. Hence, it considers all the network constraints, including line limits, voltage limits, and stability margins, are respected during simulations [102].

2.5.1. Applications of NPM

Applications of NPMs are diverse and essential to the modern power system. One of the major applications is in stability studies, whereby these models are employed to assess the stability of the system under fault and disturbance operating conditions such as post-generator trip or fault frequency and voltage deviations. In the context of MGs, the NPM is mainly applied to simulate islanding operations, investigate how DERs interact, and assess how the system responds due to load changes. Another important area where NPMs are applied is in designing control systems, where the model helps develop strategies for voltage and frequency regulation in MGs or decentralized control schemes of DGs. Moreover, NPM plays a vital role in real-time simulation. This model is used to test protective devices, control algorithms, and grid modernization technologies [94, 103, 104].

2.5.2. Benefits and Challenges of NPM

The advantages of the NPMs are high accuracy since the details of network topology are included, while they can be used for both steady-state and dynamic studies. Additionally, they consider the complex interconnections and configurations in large-scale power systems. Nevertheless, these models have drawbacks. These models are quite computationally intensive, especially for large systems, and require detailed data on network components and their dynamic behavior [94, 95, 104].

2.6. CONTINUOUS POWER FLOW

Continuous power flow (CPF) is an advanced analytical technique used in power system analysis to study the operational limits and behaviors of electrical networks under changing load conditions. In contrast to conventional methods for power flow, which often operate at discrete steps of load levels, CPF provides a continuous depiction of how the system responds to changes in load or generation [105, 106].

2.6.1. Features of CPF

The CPF has several important features that make the technique of CPF even more effective in power system analysis. Below are the main features of this analytical technique:

1. **Continuous Variation of Load:** CPF permits the study of how power flows through the network change continuously rather than in district moments by allowing loads and generation levels to be gradually adjusted. This is particularly helpful when analysing the full range of operational conditions [107, 108].
2. **Equations of Load Flow:** the **technique** employs load flow equations, which are expressed as a function of load levels and system parameters so that with changes in conditions, the calculation of power flows over the network can be done [109].
3. **Stability and Limits:** CPF is valuable for determining the operational limits of power systems, including voltage stability and thermal limits of transmission lines, and generator capability. It helps to provide certain critical points where the system may become unstable or constraints violated [110].
4. **Sensitivity Factors:** this technique can be **used** for sensitivity analysis of power flows with respect to variations in system parameters such as line

capacities, generation level, and load characteristics. Infrastructure investments and operational choices can be guided by this understanding [111].

5. **Renewable Energy Integration:** the integration of **RESs** is continuously rising; CPF serves as a useful method to study the impact of variable generation on system reliability and performance. This approach is helpful when the RES's output is unpredictable or varies over time [112].

2.6.2. Applications of CPF

The CPF has many applications in power system analysis, providing valuable insights and enhancing operational strategies for various domains. CPF is applied in dynamic simulations, where transient behavior is modelled to allow operators to analyse how the system responds to sudden changes in generation or load [113]. CPF supplements optimal power flow studies by providing continuous power flow information that helps in optimizing generation dispatch while considering network constraints. In contingency planning, CPF evaluates the system performance in response to equipment loss or total failure, enabling proactive actions to maintain system reliability. By continuously analysing voltage profiles across the network, CPF helps identify areas prone to voltage collapse and assists in developing mitigation strategies. Moreover, CPF can evaluate the resilience of power systems against extreme events, such as natural disasters or cyber-attacks, by modelling various scenarios and the impact on system operations [114, 115].

2.6.3. Benefits and Challenges of CPF

The advantages of CPF involve several benefits in power systems analysis. It offers high accuracy, presenting a more detailed and specific representation of system behavior under different conditions compared to conventional methods. CPF enables real-time analysis, allowing for real-time monitoring, and decision-making based on current operations. Additionally, it enhances long-term planning by evaluating the impact of various configurations or system upgrades on the overall performance. In many cases, the mathematical formulation and the computational requirements of CPF are more demanding than traditional approaches, requiring advanced numerical techniques. Besides, its accurate implementation necessitates comprehensive data about the network's topology, component ratings, and operational characteristics, which can result in significant data requirements [115, 116].

2.7. MODEL PREDICTIVE CONTROL

MPC is a sophisticated control approach that uses a model of the system to predict its future behavior and make control decisions. Capable of handling multi-variable systems with various constraints, MPC becomes a strong tool for the real-time control of complex systems [117]. Power systems widely adopt MPC for flexibility, predictive capabilities, and optimizing performance over time. Its predictive nature enables it to forecast the state of the power system based on the current conditions. This allows the operator to take timely preventive action and anticipate disturbances [118, 119]. In addition to predictive capabilities, MPC solves an optimization problem at each time step, minimizing a cost function related to energy losses or voltage deviations while considering system constraints, such as generation limits and transmission capacities. It effectively manages operational constraints related to power balance, voltage stability, and generation limits. Moreover, MPC can address multiple objectives simultaneously, including cost reduction, emission control, and stability of the system, making it a flexible option for managing multiple objectives [37, 120-122].

Application-wise, the key responsibility of MPC lies in load frequency control, where it balances supply and demand in real-time to keep the grid frequency within stable limits. Additionally, it acts in voltage control to maintain voltage magnitude within safe operational limits, especially during peak load or disturbance conditions. MPC optimizes the balance between renewable and conventional generation and consumption in MG energy management, considering factors like energy storage and market prices. Moreover, it is used in demand response management to enhance the interaction between energy demand and supply by managing flexible loads using real-time pricing [123, 124].

A straightforward MPC-based MG inverter control structure is shown in Figure 1.2. In this figure, the measured system variable x, current, voltage, or frequency, is passed through the predictive model to forecast the future system output $\hat{x}$. The forecasted output is then processed by an optimization algorithm to determine the optimal control input $u(t)$ that minimizes a defined cost function by the control objectives. The desired output trajectory that the system aims to follow is represented by the reference signal x^*.

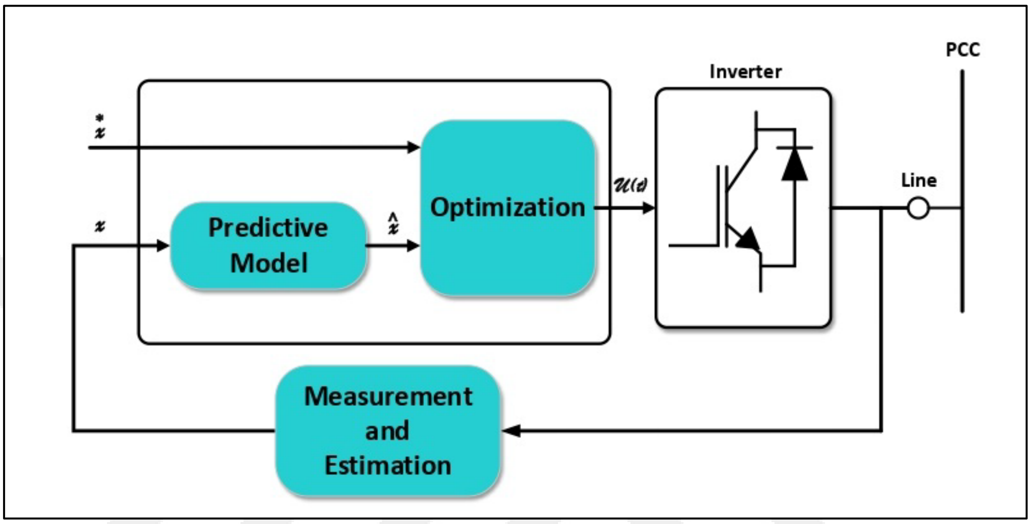


Figure 2.1. Block diagram and strategy of MPC for controlling MG

2.8. NONLINEAR MODEL PREDICTIVE CONTROL

Nonlinear model predictive control (NLMPC) extends traditional MPC to handle nonlinear system dynamics, which is a common feature in many power systems. Traditional MPC normally assumes systems are linear, while NLMPC incorporates nonlinear models. Thus, NLMPC is more accurate for systems with complex dynamics, such as power grids with RESs, electric vehicles, and dynamic variations in load. NLMPC utilizes nonlinear mathematical models of the power system dynamics for control when standard linear model-based approaches fail to meet the desired performance [125, 126]. This method provides superior control when dealing with naturally nonlinear systems, as seen in power grids where outputs are prone to fluctuation due to the variability in RESs, such as wind turbines and solar panels [127].

Furthermore, NLMPC has the capability to optimize system performance in scenarios where nonlinear constraints need consideration, demonstrating that linear assumptions are not good enough [128, 129]. The applications of NLMPC in power systems involve MG control, where the dynamic interactions among RESs, loads, and energy storage systems have to be managed effectively. This includes optimizing DGs, which involves regulating the output of wind turbines and solar panels to achieve maximum efficiency while ensuring grid stability. Regarding energy storage management, NLMPC optimizes battery charge cycles according to real-time grid demands and renewable generation forecasts [130, 131].

2.9. UNCERTAINTIES IN RENEWABLE ENERGY SOURCES AND LOAD DEMANDS

The uncertainties in the RESs and load demands pose significant challenges for power system management and operation. Constraints posed by the fluctuations of renewable resources and load demands are major obstacles to power system management and operation [132, 133]. Variability is one of the main factors associated with RESs, such as wind and solar, which are two intermittently available sources. For instance, wind speed fluctuates throughout the day, and solar generation varies with weather patterns and different times of day. This can lead to significant variations in power production, making forecasting the energy supply a challenging task [133-135].

Moreover, uncertainties related to RESs and load demands demonstrate significant variability. During the day, dynamic consumption patterns change due to various circumstances, including social behavior, the time of day, and the weather. For instance, electricity demand peaks in the morning and evening while it is off-peak during other times when the demand is low. Seasonal variations in load demand depend on the extreme weather that entails higher consumptions of electricity either for heating in winter or cooling in summer [136-138].

Besides, variability in load demand can be attributed to economic causes. Changes in industrial output, business activities, and consumer behavior can lead to sudden fluctuations in electricity demand. Additionally, unexpected events like natural disasters, public holidays, or major social events can cause sudden changes in the load demands. This makes forecasting even more complex. This inclusion of smart

technologies, such as smart thermostats and electric vehicles, adds further complexity by introducing variability based on user preferences and behavior [138-140].
Such uncertainties have far-reaching implications, threatening grid stability and the balance between supply and demand. Inaccuracies in forecasting lead to inefficient power system operations, which increase costs for utilities and consumers. Therefore, mitigating these different sources of uncertainty is essential for the successful integration of variable RESs into the power systems. The development of advanced forecasting techniques, flexible operational strategies, and innovative technologies will be necessary for maintaining grid stability and efficiency, ensuring reliable energy delivery in a rapidly changing environment [141, 142].

In order to overcome these obstacles, sophisticated forecasting methods, adaptive operational approaches, and modern technologies are essential in the operation of the power grid. Monte Carlo methods are an effective tool in managing random fluctuations in renewable energy and load using random sampling for replicating the process. This enables the management of a variety of outcome scenarios, which is useful for forecasting and improving the quality of decisions made [143, 144]. Moreover, it is critical to comprehend the probability distribution functions (PDFs) of many variables, including variations in demand and generation capacity. These PDFs are useful for describing the likelihood and variability of certain outcomes. Power system operations can more effectively predict variations and develop plans to lessen their consequences by precisely modelling these PDFs [145, 146].

2.10. SUMMARY AND FUTURE DIRECTIONS

Despite extensive research on power systems and MGs, particularly their management and control using MPC, large gaps in research still exist. Table 2.1 compares the suggested approach with state-of-the-art techniques, highlighting its advantages in system complexity, stability, real-time performance, and system efficiency.

Table 2.1. Comparison of Proposed Method and State-of-the-Art Techniques.

Aspect	References	This

	[42]	[43]	[45]	[47]	[48]	Paper
System Complexity	Moderate, lacks operational reliability consideration	High, but excludes RESs and ESS	High, with significant computational costs	High, focused on individual MGs	High, dependent on data quality	High, with detailed NLMPC framework
Stability	Limited, overlooks operational reliability	Limited, excludes RESs	Moderate, high computational costs	Advanced, but focuses on single MGs	Advanced, depends on data-driven accuracy	Improved through PNLMPC approach
Real-Time Performance	Good, but lacks policy change consideration	Good, but lacks RESs and ESS	Moderate, not feasible for real-time due to high costs	Excellent, focuses on MG control	Good, depends on model quality and data	Excellent, optimized for real-time control
System Efficiency	Moderate, does not consider all operational factors	Moderate excludes critical components	Moderate, costly and untested in practice	High, but focuses on individual systems	High, limited by data-driven model quality	High, reduces cost by significant margins

Most studies tend to ignore important conditions and details. The majority of these studies do not take into account the network's real-life conditions, and they focus on theoretical scenarios that do not accurately reflect actual working conditions. Additionally, some prioritize cost reduction, focusing exclusively on economic aspects while neglecting essential technical and model preservative aspects of the system. This thesis aims to address these gaps by providing new, practical solutions to the following challenges:

1. Integration of a preserving network model for comprehensive system representation.
2. Implementation of CPF considerations using NLMPC.
3. Real-time and fast response mechanisms improve the responsiveness of the optimal proposed NLMPC (PNLMPC) model.
4. Simultaneous examination of both technical and economic aspects, ensuring a holistic understanding and optimization approach.
5. The unpredictable behavior of wind speed and solar radiation is accurately modelled using the reduction technique based on Monte-Carlo Simulation.

These distinguishing features highlight the novelty and further capabilities of this research to advance the state of the art in power systems and MG studies.

PART 3

RESEARCH METHODOLOGY

In this chapter, the modelling of DERs, including both rotating and non-rotating sources, is presented. Accurate modelling of these components provides the key design of high-level control strategies. Among these, the NLMPC plays a central role in managing the MG and enabling effective power sharing in the system. This framework ensures optimal performance despite changes in DG capacity or load demand, while maintaining technical reliability, improving energy efficiency, and ensuring a consistent power supply to critical loads.

3.1. INTRODUCTION

MGs, characterized by localized energy systems with distributed generation sources and controllable loads, have emerged as a crucial solution for enhancing grid resilience and advancing sustainability [35, 66]. As the demand for efficient and reliable energy solutions continues to rise, the optimization of MG control becomes imperative. MPC offers a promising framework in this endeavour, providing a dynamic and forward-thinking approach [147, 148]. However, the evolution to NLMPC presents an even more sophisticated means of MG control [149]. NLMPC not only enables anticipation and adaptation to future system behaviors but also effectively manages nonlinearities, constraints, and uncertainties inherent in MG operations [150, 151]. The development of an effective NLMPC framework involves preserving network structure, addressing the complexities of linear and non-linear loads, and adeptly managing various resources, including energy storage devices. By seamlessly handling CPF and optimizing assets within the MG, NLMPC holds the potential to significantly enhance MG performance, promoting resilience, flexibility, and sustainability in power systems.

The majority of DERs, which include DGs and RESs, are used in small electrical power grids known as MGs. Functionally, MGs can be categorized as either grid-connected, islanded, or in transition between these two states [2, 35, 36]. MPC has received significant attention in power systems engineering, particularly in MG energy management. Several factors contribute to this interest. Firstly, MPC is well-suited for systems heavily reliant on demand and renewable energy generation forecasts, as it is based on predictions of future system behavior [37]. Secondly, the system becomes more resilient to uncertainty, as MPC provides a feedback mechanism that allows for real-time adjustments to be made [38]. Lastly, MPC effectively manages power system constraints, including generator capacity and load balance, in the tertiary control layer [39].

Numerous studies have explored the use of MPC for effective power system management. The Economic Model Predictive Control (EMPC) approach has gained prominence as an effective solution for optimizing economic dispatch and integrating various energy storage systems [40, 41]. However, reference [40] does not consider stochastic scenarios in handling wind power uncertainty and is oblivious to market dynamics and fluctuation in pricing. Similarly, reference [41] does not deal with the issues of applying various models to predict load demand and renewable energy generation. Based on [42] the authors have suggested a real-time multi-objective load dispatch strategy for biomass heat and power cogeneration using MPC. While this paper gives a workable method to achieve real-time control, it overlooks operational reliability and transition times inherent in plants that convert biomass. The fact that the research does not consider independent variables that could have an impact on the performance of the proposed load dispatch control method, in view of external influences such as market dynamics or state policy changes, is overlooked. Furthermore, in reference [43], a distributed EMPC approach based on imprecise dual minimization is explored to tackle real-time economic dispatch problems. It is noteworthy, however, that the case study in this reference does not incorporate renewable generators and battery storage devices.

In this respect, the authors of reference [44] have proposed an optimization scheme for a hybrid model predictive control approach that incorporates weather prediction using the Weather Research and Forecasting (WRF) model. New rules in this setting have been introduced to deal with special needs of connection and disconnection, like minimum connection times and maximum connection frequencies. While the proposed model has been validated through simulations using real weather data, it has not yet been applied to any real MG. Additionally, the computational costs for this framework are high, and no provisions have been made for future policy changes related to grid connection. In [45] , an approach is presented for integrating wind power into system operation in real-time using an MPC scheme, which addresses uncertainty and optimizes economic dispatch. Although it manages uncertainties in wind power, it does not sufficiently account for additional uncertainties arising from demand response programs due to the unpredictable behavior of customers. Reference [46] proposes a two-layer hierarchical approach using MPC to gain better cost savings and energy efficiency for large commercial HVAC systems. The research emphasizes the challenges of real-time control for both cost and economic dispatch problems. While this work introduces hierarchical decomposition for MPC, its evaluation is done mostly based on sample optimizations and simulation results and is lacking in terms of wide validation in the real world. As emphasized by [47], NLMPC emerges as a promising approach for real-time MG control, providing a specialized solution to navigate the intricate and dynamic characteristics of DERs. While NLMPC can effectively address multiple control objectives, enhancing overall MG operation, it's important to note that this research focuses explicitly on controlling individual MGs rather than interconnected systems. Therefore, the NPM wasn't considered in this study. Reference [48] introduces a data-driven NLMPC framework tailored for MG control. This framework adeptly captures the intricate and dynamic behavior of DERs through a data-driven approach leveraging Sparse Regression (SR). It's worth noting that the accuracy of this data-driven model hinges on the quality and quantity of available data used to train the SR model. While the framework demonstrates robust performance under realistic load patterns, underscoring its relevance for practical MG applications, it's important to acknowledge that it does not incorporate the NPM. As noted in [49], NLMPC demonstrates its capability to efficiently manage optimal energy distribution within interconnected multi-node MGs equipped with energy storage. By creating a virtual pool of distributed energy storage, NLMPC optimizes energy allocation and minimizes wear on storage devices. Additionally, the controller adeptly navigates diverse scenarios, including fluctuating weather conditions, varying load demands, and changing storage levels. However, it's important to note that the NPM does not directly apply in this specific context.

Current studies often overlook essential conditions and specific network details. Most of these studies don't consider the real-life conditions of the network; they tend to stick to theoretical scenarios, which don't truly reflect the actual working conditions. Additionally, many of them prioritize cutting costs, emphasizing economic aspects, and ignoring the crucial technical and model preservation aspects of the system. This paper aims to bridge these gaps by introducing new and practical solutions to address the following shortcomings.

1. Integration of a preserving network model for comprehensive system representation.
2. Implementation of CPF considerations using NLMPC.
3. Real-time and fast response mechanisms, improve the responsiveness of the optimal proposed NLMPC (PNLMPC) model.
4. Simultaneous examination of both technical and economic aspects, ensuring a holistic understanding and optimization approach.
5. The unpredictable behavior of wind speed and solar radiation is accurately modelled using the reduction technique based on Monte-Carlo Simulation.

These distinctive features underscore the novelty and superior capabilities of this research in advancing the state-of-the-art in power systems and MG studies.

3.2. CONCEPTUAL MODEL OVERVIEW FOR NETWORK DYNAMICS

MPC incorporates diverse techniques characterized by variations in model type, objective function, and solution approach [152, 153]. Various MPC formulations can be employed for effective MG management [154]. In this study, NLMPC serves as a central controller, regulating each resource by adjusting the load under varying network conditions. This controller supervises technical aspects and optimizes critical parameters like frequency and voltage, as depicted in Figure 3.1 and Figure 3.2, while simultaneously minimizing costs.

Figure 3.1 illustrates the NLMPC as the central controller in an islanded MG. The MG includes a mix of rotating and non-rotating resources, including photovoltaic panels, wind turbines, diesel generation, and battery storage. The NLMPC optimizes power flows and control setpoints among various DGs and loads. The configuration comprises three inverters dedicated to the photovoltaic system, wind turbines and battery storage, a diesel generator, and local loads. Moreover, the diesel generator is directly connected to the MG. In this setup, Inverter 1 (associated with the photovoltaic system) acts as the PV bus, and Inverter 2 serves as the V/F bus, and Inverter 3 (associated with battery storage) functions as the PQ bus when in charging mode and as the PV bus when in discharging mode. The NLMPC manages the operation of the inverters and the diesel generator to ensure that power generation meets load demand while maintaining the required voltage and frequency levels.

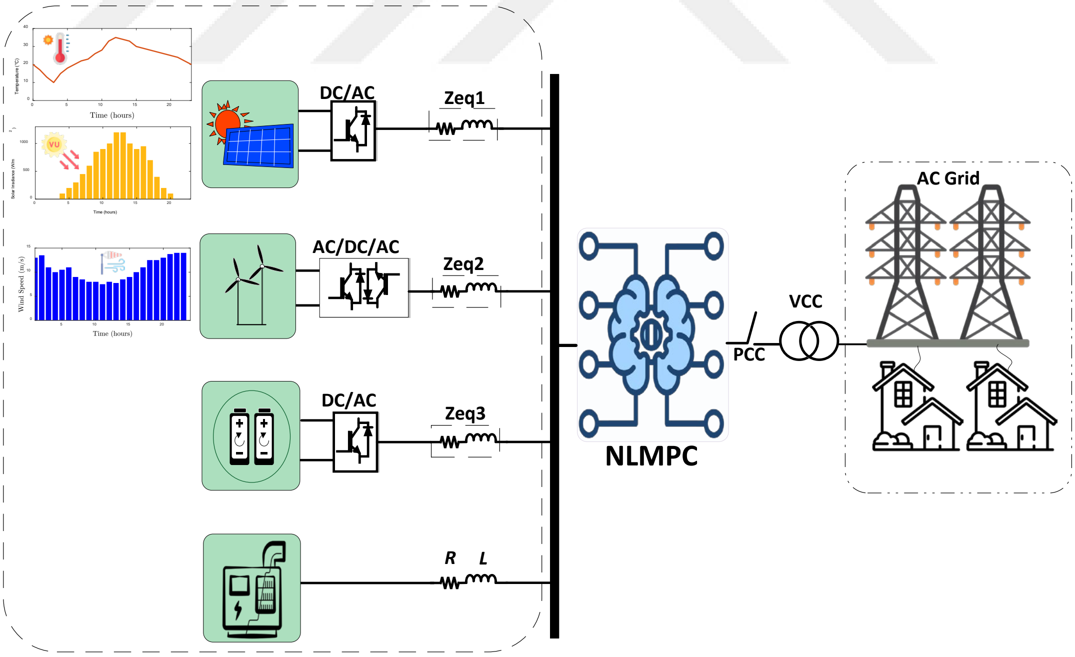


Figure 3.1. Conceptual model of network and islanded MG.

Figure 3.2 presents the configuration of the grid-connected MG under study, which incorporates a combination of both rotating and non-rotating energy resources. These include a utility grid connection, photovoltaic (PV) panels, a diesel generator, and battery energy storage. The system is designed with three inverters, each dedicated to a specific power source or function: the utility grid, the PV system, and the battery storage. Additionally, the diesel generator is directly integrated into the MG without the need for an inverter.

The inverters play crucial roles in managing the power flow and stability of the system. Inverter 1, which interfaces with the utility, operates as a voltage-frequency (Slack) bus, maintaining the reference voltage and frequency for the MG. Inverter 2, linked to the PV system, functions as a PV bus, regulating active power generation from the photovoltaic panels. Inverter 3, connected to the battery storage, has a dual role: it operates as a PQ (active and reactive power) bus during the battery's charging phase and switches to a PV bus during the discharging phase, controlling the battery's contribution to the grid. This flexible operation of Inverter 3 allows for efficient energy management and enhances the resilience of the MG under varying load and generation conditions.

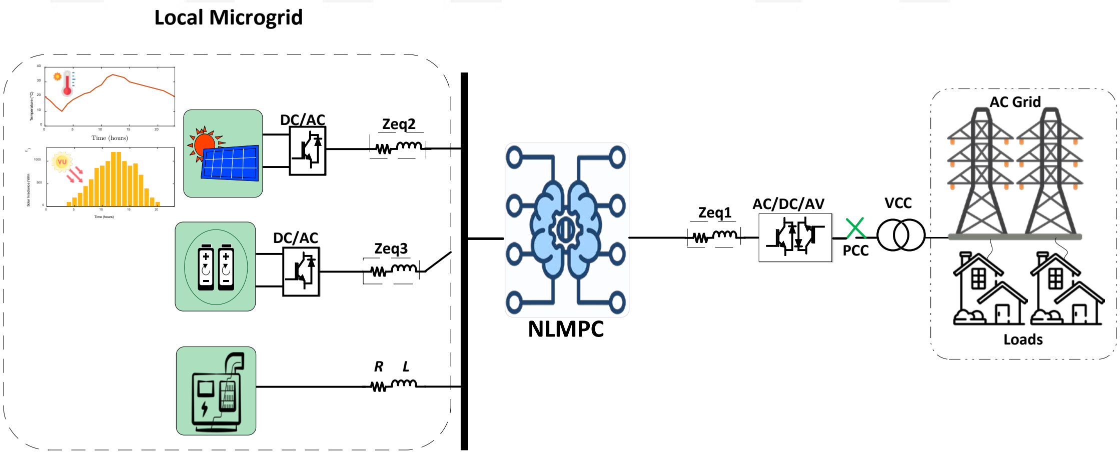


Figure 3.2. Conceptual model of network and grid-connected MG.

3.3. OPTIMAL NLMPC CONTROL METHODOLOGY

The NLMPC is a key component of the MG and is responsible for coordinating the operation of various DGs and loads to achieve optimal control. Using a nonlinear model-based approach, the NLMPC effectively anticipates and manages the dynamic behavior of MGs. It optimizes power flow between DGs and loads, minimizing energy losses. Moreover, the NLMPC enhances adaptability by incorporating uncertainty models to forecast variable RESs and load fluctuations, thereby improving system resilience. This framework keeps on performing optimally with changes in DG addition or load variations. As a central control element, the NLMPC manages the operation of all MG components, maintaining voltage and frequency stability, optimizing energy efficiency, and ensuring a reliable power supply to the loads. Given that energy storage is a pivotal component of MGs, their dynamic models are commonly expressed as state-space equations, with the state variable x(t) representing the charge level of the batteries. This implies that state-space models can effectively define the predictive control problem, rendering state-space MPC a promising choice for both grid-connected and islanded MG management. Moreover, this formulation is well-suited for handling multi-variable systems, a common scenario in both grid-connected and islanded MG. To model the behavior of a linear system, the following equations are employed:

$$\begin{cases} X(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{3.1}$$

MGs are often multi-input multiple-output (MIMO) systems. MIMO systems have m-dimensional input vectors *u(t)* and n-dimensional output vectors *y(t)*. Matrix C equals identity because the output *y(t)* typically follows the state *X(t)* [155]. MPC computes a future control sequence over a finite horizon by utilizing the system's current state, input, and output measurements, along with its model at each sampling instant. This control series meets constraints on the control action while optimizing a specified performance index. The control goal is to identify a series of control inputs across a specific prediction horizon, based on the current measurement, that satisfies a particular objective function and constraints. The control sequence described above will provide a predicted series of state vectors, which may be utilized to compute the expected sequence of system outputs. With the use of this knowledge, the system may be controlled, and the procedure is then repeated with the state measurement of the following time step acting as an initial condition to calculate the control input. Typically, the major objective is to penalize the control effort required to achieve the future output by tracking a certain reference signal along the prediction horizon. Hence, the following mathematical explanation of the MPC's objective function and constraints are possible:

$$min\, J\left(N_p\right) = \sum_{j=1}^{N_p}\left[\|\hat{y}(t+j|t) - r(t+j)\|_R^2 + \|\Delta u(t+j-1)\|_Q^2\right] \quad (3.2)$$

$$s.t{:}\begin{cases} f\left(\hat{y}_t^j, \hat{x}_t^j, \hat{u}_t^j\right) = 0 \\ g\left(\hat{y}_t^j, \hat{x}_t^j, \hat{u}_t^j\right) \leq 0 \end{cases} \quad (3.3)$$

Where, the $\hat{y}$ is a normalized function encompassing various objectives, including voltage optimization, frequency management, power losses reduction, and cost minimization for the network. *R* and *Q* are diagonal positive definite weighting matrices, and functions *f* and *g* indicates the equality and inequality constraints, respectively [156].

Hence, the objective function for the PNLMPC problem would be:

$$min\, J\left(N_p\right) = \sum_{j=1}^{N_p}\begin{bmatrix}\|\hat{y}(t+j|t) - r(t+j)\|_R^2 \\ +\|\Delta u(t+j-1)\|_Q^2\end{bmatrix} + \left[c\hat{y}(t+j|t)\right]\right] \quad (3.4)$$

where *c* represents the contribution cost for the state variables [157], and the constraints would be the same as regular MPC. In fact, the objective function incorporates all technical and economic parameters and conducts optimization accordingly. Additional details regarding these aspects will be presented in the subsequent sections.

3.4. PROBLEM FORMULATION

This section outlines the goals and limitations of the proposed algorithm. The objective functions revolve around technical considerations, including power loss, operating cost, frequency and voltage stability, voltage deviation, and the management of storage devices. Following this, the section delves into the mathematical formulations and constraints associated with modelling both rotating and non-rotating resources. In the context of real-time applications, a method's efficacy is measured by its ability to promptly estimate stability margins without relying on post-fault information, coupled with a low computational cost. However, from a real-time perspective, recalculating the system's operating point becomes challenging and time-consuming due to system topology changes resulting from disturbances. Network reduction models were prevalent in the initial stages of direct method development. In the 1980s, the concept of NPMs emerged to overcome the drawbacks associated with network-reduction models [94]. By employing a NPM, the network structure is conserved, leading to the designation of the corresponding NLMPC function as a "structure-preserving" energy function. In direct comparison with network-reduction models, Network-preserving models offer several advantages for direct stability analysis [93, 95, 158]:

1. In system modelling, it preserves the original network topology, allowing for a more realistic representation of power system components, including dynamic load behavior (voltage and frequency variations) at load buses and detailed generator models.
2. In terms of the energy function, the transfer conductance of the preserving model significantly outperforms that of network-reduction models. This results in a numerical energy function that closely approximates the exact energy function.
3. From a computational standpoint, sparse matrix techniques can efficiently solve the nonlinear algebraic equations involved in the model.

In this study, the network-preserving model employs CPF, which is implemented through equations (3.5) and (3.6).

$$P_i = \sum_{j=1}^{n} |V_i||V_j|\,|Y_{ij}|\,cos\big(\theta_{ij} - \delta_i + \delta_j\big) \tag{3.5}$$

$$Q_i = -\sum_{j=1}^{n} |V_i||V_j|\,|Y_{ij}|\,sin\big(\theta_{ij} - \delta_i + \delta_j\big) \tag{3.6}$$

Where, Y_{ij} is the matrix representing the connectivity between bus *i* and bus j.

The PNLMPC framework is specifically designed to address the inherent uncertainties in MG operation, including variations in renewable energy generation, unpredictable load changes, and potential equipment failures. As Figure 3.3 and Figure 3.4 depict an inverter model with an LC filter, the PNLMPC employs a model-based predictive control strategy in both islanded MG and grid-connected MG. This strategy relies on a nonlinear mathematical model of both gid-connected MG and islanded MG to forecast and optimize system behavior over a future time horizon. By incorporating the nonlinear dynamics of various components, such as inverters, the diesel generator, and energy storage, the PNLMPC captures complex interactions more effectively and makes more informed control decisions. The optimization process accounts for factors like renewable energy availability, battery state-of-charge, load forecasts, and system constraints, aiming to achieve objectives such as cost minimization, emissions reduction, and enhanced reliability. These systems operate under slower droop control, as shown in Figure 3.5.

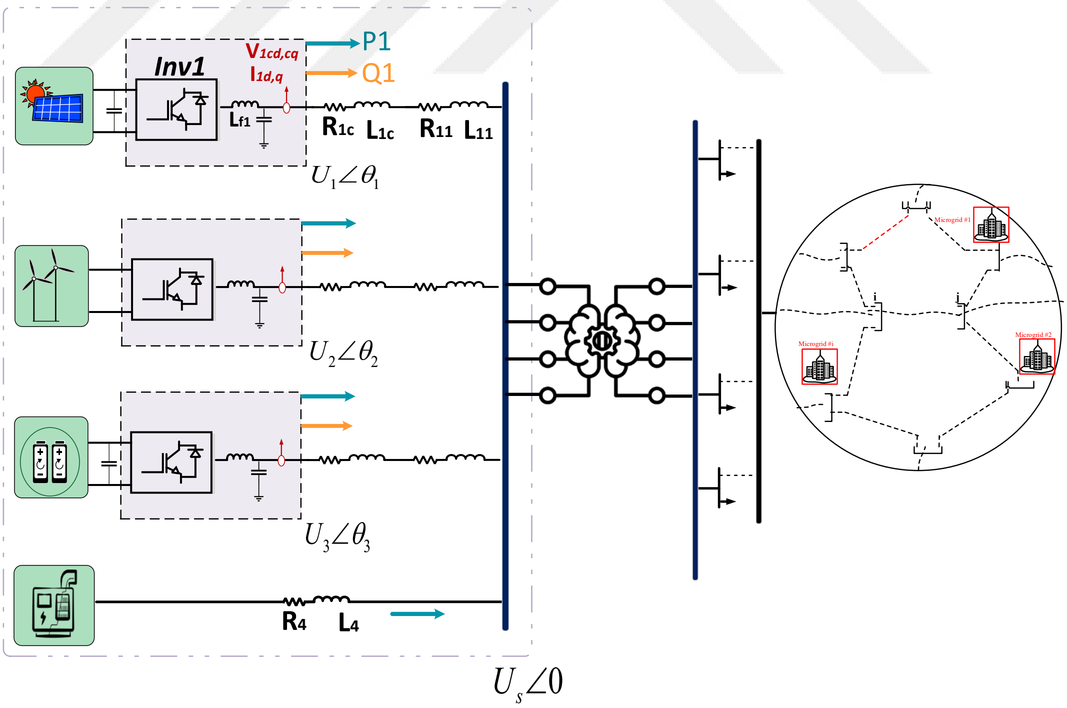


Figure 3.3. Illustration of the studies inverter mode in islanded MG.

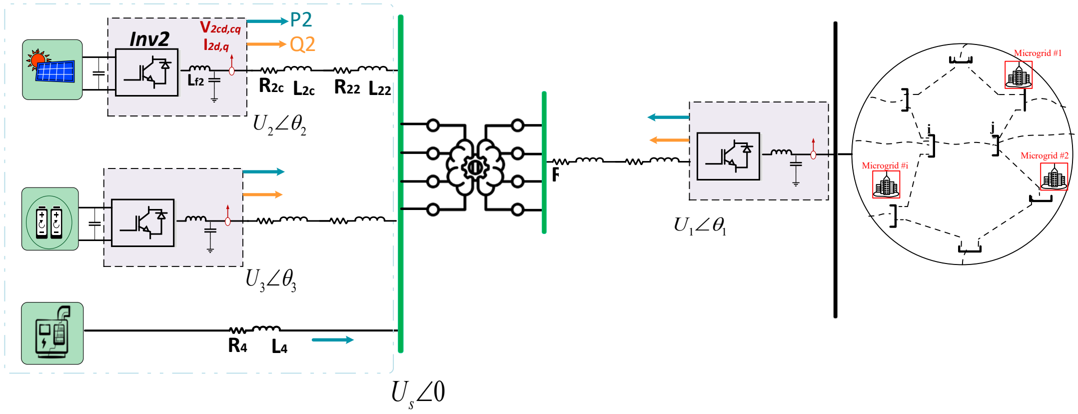


Figure 3.4. Illustration of the studies inverter model in grid-connected MG.

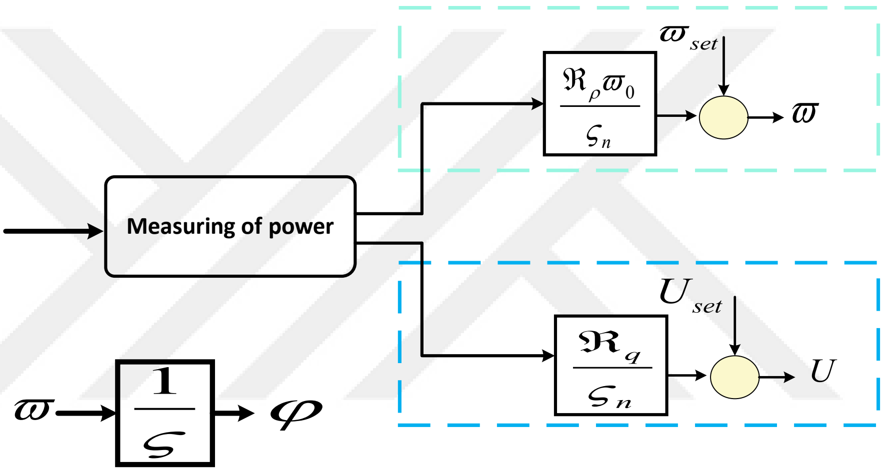


Figure 3.5. The inverter droop controller.

The effective terminal voltage and phase angle of the inverter, post-LC filter passage, are denoted in accordance with this model. By employing this representation, system dynamics can be accurately characterized using the inverter's terminal states (angle, frequency, and voltage) and the line currents as dynamic variables without the necessity of considering the internal states of the inverter. This methodology is based on a 5th-order electromagnetic (EM) model, encompassing three inverter-related states (angle, frequency, and voltage) and two line-related states (the two components of the current phasor). The equations detailing this model in the *dq* reference frame are as follows:

$$\dot{\varphi} = \varpi - \varpi_0 \tag{3.7}$$

$$\tau\dot{\varpi} = \varpi_{set} - \varpi - \frac{\Re_p \varpi_0}{\varsigma_n} P_{measurment} \tag{3.8}$$

$$\tau\dot{U} = U_{set} - U - \frac{\Re_q}{\varsigma_n} Q_{measurment} \tag{3.9}$$

$$L\dot{I}_d = U_{\cos\theta} - U_0 - RI_d + \varpi_0 LI_d \tag{3.10}$$

$$L\dot{I}_d = U_{\sin\theta} - U_0 - RI_d + \varpi_0 LI_d \tag{3.11}$$

In this context, the variables U and φ represent the effective terminal voltage and phase angle of the inverter, respectively, once they pass through the LC filters. The variable ϖ denotes the frequency of the inverter. Additionally, the variables I_d and I_q represent the dq-frame components of the inverter's output current. The equations (3.8) and (3.9) describe the behavior of the terminal voltage and frequency, respectively. These equations incorporate the influence of low-pass filters in the inverter power control system, which is characterized by the bandwidth $\varpi_c = \tau - 1$, and the values of $\Re_p$ and $\Re_q$ are the frequency and voltage droop gains, respectively.

Moreover, ς_n denotes the inverter rating, while ϖ_{set} and $U_{set}$are the set points of frequency and voltage controllers, respectively, and they are considered as inputs of the inverter. It is noteworthy that both ϖ and ϖ_0 are considered to be measured in rad/s. The expressions for $P_{mearsurment}$ and $Q_{mearsurment}$ are given by $P_{mearsurment} = \frac{3}{2} UI_d$ and $Q_{mearsurment} = \frac{3}{2} UI_q$.

On the other hand, equations (3.10) and (3.11) capture the electromagnetic dynamics of the complex current $I(t)$. The variables $L = L_c + L_l$ and $R = R_c + R_l$ represent the combined inductance and resistance of the connection, respectively, as observed at the inverter terminal.

3.4.1. Modelling of Photovoltaic Panels

Through the utilization of photovoltaic panels, the generation of power can be assessed utilizing the equation:

$$P_{PV}^{t,S}(SR^{t,S}) = N_{PV} \times FF \times V^{t,S} \times I^{t,S} \begin{cases} \{\forall t \in T \\ \forall s \in S \end{cases} \tag{3.12}$$

The generation of electricity through photovoltaic panels $P_{PV}^{t,S}$ relies on changes in solar radiation $SR^{t,S}$, ambient temperature AT^{t},time t based on hours, and particular scenario (s). A comprehensive examination of these factors, along with other pertinent attributes, is thoroughly discussed in the reference [96].

$$\begin{cases} FF = \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{SC}} \\ V^{t,S} = V_{OC} - Kv\left(AT^{t} + SR^{t,S}\left(\frac{N_{OT}-20}{0.8}\right)\right) \\ I^{t,S} = SR^{t,S}[I_{SC} + Kv(T^{t,S} - 25)] \end{cases} \tag{3.13}$$

3.4.2. Modelling of Wind Turbine

The power produced by a wind turbine depends on both the wind speed and the specific type of wind turbine, as described by the following equation [159].

$$P_{Wind\ \text{turbine}}^{T,S}(\nu_{T,S}): \begin{cases} 0 \rightarrow if \begin{cases} \nu_{T,S} \leq \nu_{IN}^{C} \\ or \\ \nu_{T,S} \geq \nu_{OUT}^{C} \end{cases} \\ \alpha + \beta \times \nu_{T,S} + \gamma \times (\nu_{T,S})^{2} \rightarrow if \begin{cases} \nu_{IN}^{C} \leq \nu_{T,S} < \nu_{R} \\ \nu_{R} \leq \nu_{T,S} < \nu_{OUT}^{C} \end{cases} \end{cases} \tag{3.14}$$

Where $P_{Wind\ \text{turbine}}^{T,S}$ represents the generated power, and ν_{IN}^{C} denotes the cut-in wind speed, indicating the lower threshold at which the wind turbine can generate power. Conversely, ν_{OUT}^{C}represents the cut-out wind speed, signifying the upper limit beyond which the wind turbine stops generating power to prevent potential damage. Moreover, α, β, and γ collectively represent the coefficients of the wind turbine. Various wind turbine models may employ distinct mathematical expressions derived from empirical data and theoretical considerations.

3.4.3. Modelling of BESS

The comprehensive modelling approach for the ESS addresses considerations for its integration and performance within the MG. This involves utilizing a set of specified equations, including equations (3.7) to (3.11), along with equations (3.15) and (3.16).

$$P_{Ch}, P_{Dis} = \pm(\frac{3}{2}U_d I_d) \tag{3.15}$$

$$\dot{E} = \eta . P_{Ch} \tag{3.16}$$

Where $\dot{E}$ represents rate of change of battery energy and h shows the coulombic efficiency. The energy stored in the battery can be calculated using the following expression:

$$E_B(t) = \begin{cases} E_B(t-1) + \left(\frac{\dot{E}}{\Delta T}\right) - \left(\frac{P_{B(t)}^{Dis}}{\Delta T}\right) . \left(\frac{1}{\eta_B^{Dis}}\right) & t > 1 \\ E_B(0) + \left(\frac{\dot{E}}{\Delta T}\right) - \left(\frac{P_{B(t)}^{Dis}}{\Delta T}\right) . \left(\frac{1}{\eta_B^{Dis}}\right) & t = 1 \end{cases} \tag{3.17}$$

Where $E_B(t)$ (kWh) represents the battery's energy level at time *t*, and $E_B(0)$ denotes the initial energy level of the battery. Notably, the charging and discharging operations of the battery energy storage system (BESS) do not occur simultaneously, so binary variables $\Im_B^{Ch}$ and $\Im_B^{Dis}$ are employed for operational decision-making. Additionally, the binary variables constrain the BESS charging/discharging capacity. Considering the constraints posed by degradation, equation (3.21) sets limits on the BESS's lower and upper energy levels.

$$0 \leq P_{B(t)}^{Ch} \leq P_{B,max}^{Ch_B^{Ch}} \tag{3.18}$$

$$0 \leq P_{B(t)}^{Dis} \leq P_{B,max}^{Dis_B^{Dis}} \tag{3.19}$$

$$\Im_B^{Ch} + \Im_B^{Dis} \leq 1 \tag{3.20}$$

$$E_{B,min} \leq E_B(t) \leq E_{B,max} \tag{3.21}$$

$$\dot{SoC} = \frac{\dot{E}}{E} \tag{3.22}$$

$\dot{SoC}$ relates the rate of change of state of charge and the total battery energy is described by E.

3.4.4. Modelling of Diesel Generator

Alterations in active power have a substantial impact on the overall system frequency, with reactive power displaying a comparatively lower sensitivity to frequency variations, predominantly depending on changes in voltage magnitude. As a result, active and reactive power are managed by distinct control mechanisms. The load frequency control (LFC) loop oversees active power and frequency, while the automatic voltage regulator (AVR) loop maintains control over reactive power and voltage magnitude. The importance of LFC has grown with the expansion of interconnected systems, facilitating their efficient operation. In this study, our focus is exclusively on the LFC loop for generators, while the AVR loop is disregarded. Consequently, it is assumed that the diesel generator solely contributes to the distribution of active power. LFC is implemented for every generator in a connected power system. Figure 3.6 illustrates the diagram depicting the LFC loop. The controllers are configured based on a specific operational state and are responsible for managing slight changes in load requirements to ensure that the frequency remains within predefined boundaries. Minor changes in active power are predominantly influenced by alterations in the rotor angle, subsequently impacting the frequency.

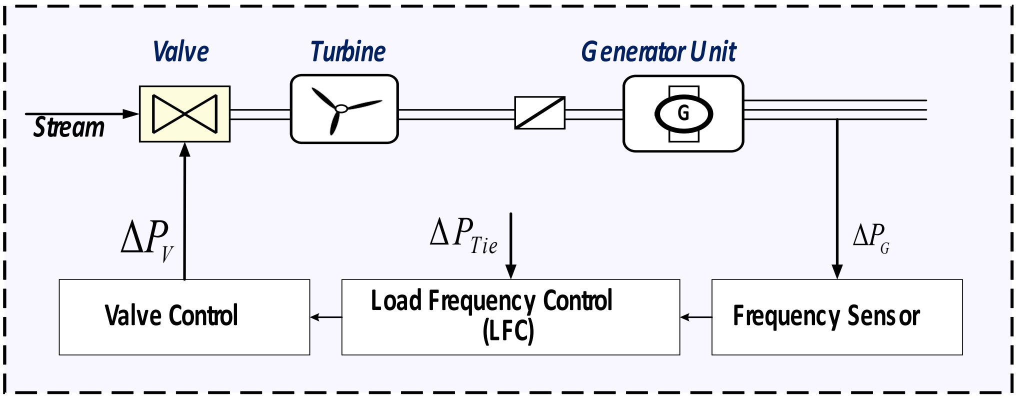


Figure 3.6. Block diagram of automatic LFC.

The explanation of the primary components of LFC, including the Governor, prime mover load, and rotating mass model, is provided as follows:

The Governor model: the input command ΔP_G is converted via a hydraulic amplifier into the steam valve position ΔP_V. The governor time constant T_G characterizes the response time of the governor, and its transfer function is given by:

$$\frac{\Delta P_V(s)}{\Delta P_G(s)} = \frac{1}{1+T_G s} \tag{3.23}$$

Prime mover model: the prime mover model serves the purpose of generating mechanical power, which can be accomplished through the utilization of various energy sources such as steam for steam turbines or water for hydraulic turbines. The prime mover model, denoted as $\Delta P_{mechanical}$, establishes a relationship between the mechanical power output and variations in the steam valve position ΔP_V. The transfer function for this model is expressed as:

$$\frac{\Delta P_V(s)}{\Delta P_G(s)} = \frac{1}{1+T_{Turbin} s} \tag{3.24}$$

Rotating mass and load model: the response of the motor load to changes in frequency can be assessed through the examination of its speed-load characteristic.

$$\frac{\Delta \varpi(s)}{\Delta P_{mechanical}(s) - \Delta P_{Load}(s)} = \frac{1}{2Hs+D} \tag{3.25}$$

Utilizing equations (3.23), (3.24), and (3.25), the LFC loop for the diesel generator can be constructed, as depicted in Figure 3.7.

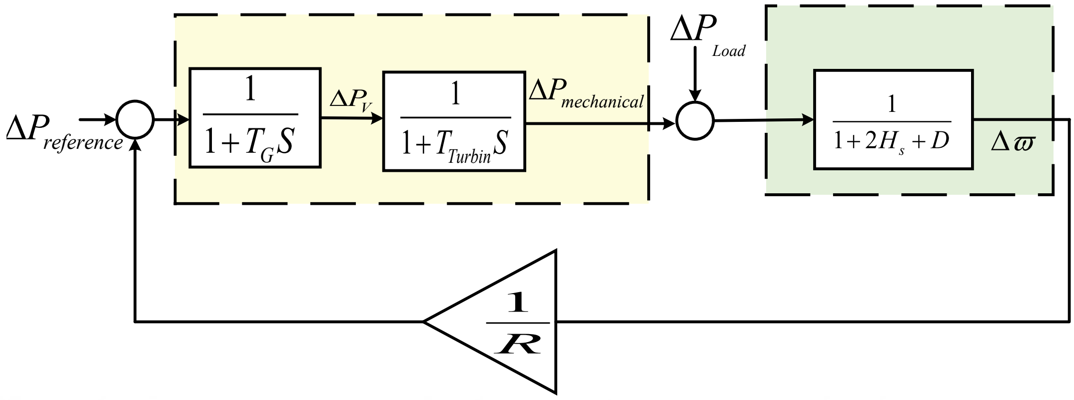


Figure 3.7. Load frequency control diesel generator.

The s-domain equations describing the block diagram can be expressed as:

$$\begin{cases} (1+T_{Turbin}s)\Delta P_V(s) = \Delta P_{reference} - \frac{1}{R}\Delta\varpi(s) \\ (1+T_{Turbin}s)\Delta P_{mechanical}(s) = \Delta P_V \\ (2Hs+D)\Delta\varpi(s) = \Delta P_{mechanical} - \Delta P_{Load} \end{cases} \tag{3.26}$$

$$\begin{cases} s\Delta P_V(s) = -\frac{1}{T_G}\Delta P_V(s) - \frac{1}{RT_G}\Delta\varpi(s) + \frac{1}{T_G}\Delta P_{reference}(s) \\ s\Delta P_{mechanical}(s) = \frac{1}{T_{Turbin}}\Delta P_V(s) - \frac{1}{T_T}\Delta P_{mechanical}(s) \\ s\Delta\varpi(s) = \frac{1}{2H}\Delta P_{mechanical}(s) - \frac{D}{2H}\Delta\varpi(s) - \frac{1}{2H}\Delta P_{Load}(s) \end{cases} \tag{3.27}$$

Transforming into time-domine, it is observed that:

$$\begin{cases} \dot{\Delta P}_V(s) = -\frac{1}{T_G}\Delta P_V - \frac{1}{RT_G}\Delta\varpi + \frac{1}{T_G}\Delta P_{reference} \\ \dot{\Delta P}_{mechanical}(s) = \frac{1}{T_{Turbin}}\Delta P_V - \frac{1}{T_{Turbin}}\Delta P_{mechanical} \\ \dot{\Delta\varpi} = \frac{1}{2H}\Delta P_{mechanical} - \frac{D}{2H}\Delta\varpi - \frac{1}{2H}\Delta P_{Load} \end{cases} \tag{3.28}$$

where in our study, $[\Delta P_V, \Delta P_{mechanical}, \Delta\varpi]^T$are states of the diesel generator and ΔP_{Load} is the input of the system. Expressing in matrix form, with $\Delta P_{reference} = 0$, the state equation becomes:

$$\begin{bmatrix} \dot{\Delta P_V} \\ \dot{\Delta P}_{mechanical} \\ \dot{\Delta \varpi} \end{bmatrix} = \begin{bmatrix} \frac{-1}{T_G} & 0 & \frac{1}{RT_G} \\ \frac{1}{T_{Turbine}} & \frac{-1}{T_{Turbine}} & 0 \\ 0 & \frac{1}{2H} & \frac{-D}{2H} \end{bmatrix} \begin{bmatrix} \Delta P_V \\ \Delta P_{mechanical} \\ \Delta \varpi \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{-1}{2H} \end{bmatrix} [\Delta P_{Load}] \quad (3.29)$$

3.5. CONTROL ORIENTED MODEL

The MG configuration under investigation includes three inverter-based DERs and a diesel generator. In grid-connected mode, the system comprises a total of 20 dynamic equations, with 3 inputs and 7 outputs. It is crucial to highlight that the system in islanded mode comprises a total of 20 dynamic equations, with 7 inputs and 7 outputs. Therefore, in both grid-connected and islanded mode the entire system can be formulated as follows:

Elements $[\omega_{set2}, u_{set2}]^T$, administering control signals for its operation. Moreover, the vector $[u_5(\kappa), u_6(\kappa)]^T$is specific to inverter 2 with elements $[\omega_{set3}, u_{set3}]^T$, providing control signals for its operation. The input $u_7^T(\kappa)$ is responsible for controlling the diesel generator, which is equal to P_L.

Inverter1:

$\chi_1(\kappa + 1) = f_1(\chi(\kappa))$

$\chi_2(\kappa + 1) = f_2(\chi(\kappa), u(\kappa))$

$\chi_3(\kappa + 1) = f_3(\chi(\kappa), u(\kappa))$

$\chi_4(\kappa + 1) = f_4(\chi(\kappa))$

$\chi_5(\kappa + 1) = f_5(\chi(\kappa))$

Inverter2:

$\chi_6(\kappa + 1) = f_6(\chi(\kappa))$

$\chi_7(\kappa + 1) = f_7(\chi(\kappa), u(\kappa))$

$\chi_8(\kappa + 1) = f_8(\chi(\kappa), u(\kappa))$

$\chi_9(\kappa + 1) = f_9(\chi(\kappa))$

$\chi_{10}(\kappa + 1) = f_{10}(\chi(\kappa))$

Inverter3:

$\chi_{11}(\kappa+1) = f_{11}(\chi(\kappa))$

$\chi_{12}(\kappa+1) = f_{12}(\chi(\kappa))$

$\chi_{13}(\kappa+1) = f_{13}(\chi(\kappa), u(\kappa))$

$\chi_{14}(\kappa+1) = f_{14}(\chi(\kappa))$

$\chi_{15}(\kappa+1) = f_{15}(\chi(\kappa), u(\kappa))$

$\chi_{16}(\kappa+1) = f_{16}(\chi(\kappa), u(\kappa))$

$\chi_{17}(\kappa+1) = f_{17}(\chi(\kappa))$

DieselGenerator:

$\chi_{18}(\kappa+1) = f_{18}(\chi(\kappa))$

$\chi_{19}(\kappa+1) = f_{19}(\chi(\kappa))$

$$\chi_{20}(\kappa+1) = f_{20}(\chi(\kappa)) \tag{3.30}$$

Where,

$$\begin{cases} \chi(\kappa) = [\chi_1^T(\kappa), \chi_2^T(\kappa), \chi_3^T(\kappa), \ldots, \chi_{20}^T(\kappa)]^T \\ u(\kappa) = [u_1^T(\kappa), u_2^T(\kappa), u_3^T(\kappa), \ldots, u_7^T(\kappa)]^T \end{cases} \tag{3.31}$$

In the considered context, the state vector $[\chi_1(\kappa), \ldots, \chi_5(\kappa)]^T$ with elements $[\theta_1(\kappa), \omega_1(\kappa), u_1(\kappa), I_{d1}(\kappa), I_{q1}(\kappa)]^T$ represents the dynamic variables of inverter number one. Similarly, the state vector $[\chi_6(\kappa), \ldots, \chi_{10}(\kappa)]^T$ with elements $[\theta_2(\kappa), \omega_2(\kappa), u_2(\kappa), I_{d2}(\kappa), I_{q2}(\kappa)]^T$ corresponds to inverter number two.

The state vector $[\chi_{11}(\kappa), \ldots, \chi_{15}(\kappa)]^T$ with elements $[\theta_3(\kappa), \omega_3(\kappa), u_3(\kappa), I_{d3}(\kappa), I_{q3}(\kappa)]^T$ corresponds to inverter number three. Furthermore, the state vector $[\chi_{16}(\kappa), \ldots, \chi_{20}(\kappa)]^T$ represents the state variables $[P_v, P_m, \omega_d]^T$ of the diesel generator.

Regarding control inputs, the vector $[u_1(\kappa), u_2(\kappa)]^T$ is linked to inverter 1, controlling its operation with elements $[\omega_{set1}, u_{set1}]^T$. The vector $[u_3(\kappa), u_4(\kappa)]^T$ is designated for inverter 2 featuring elements $[\omega_{set2}, u_{set2}]^T$, administering control signals for its operation. Moreover, the vector $[u_5(\kappa), u_6(\kappa)]^T$ is specific to inverter 2 with elements

$[\omega_{set3}, u_{set3}]^T$, providing control signals for its operation. The input $u_7^T(\kappa)$ is responsible for controlling the diesel generator, which is equal to P_L.

3.6. COST MODELING

The formulations of cost models for photovoltaic panels (PV), wind turbines, BESS, diesel generators, and the grid are expressed in equations (3.32) to (3.37). For comprehensive explanations of the symbols and variables used in these equations, please refer to references [160-162].

$$COST^{\varsigma}(t) = A_{\varsigma} + B_{\varsigma} \times P^P(t) \begin{cases} \forall t \in \\ \forall \varsigma \in [PV, Wind \text{ turbine}] \end{cases} \tag{3.32}$$

$$A_{\varsigma} = \frac{COST^{\varsigma}_{capital} \times P^{\varsigma}_{capital} \times AIR}{T_{life} \times 365 \times 24 \times CF_{\varsigma}}; B_{\varsigma} = COST^{O\&M}_{\varsigma} \rightarrow \forall \varsigma \in [PV, Wind \text{ turbine}] \tag{3.33}$$

$$COST^{BESS}(t) = A_{BESS} + B_{BESS} \times |P^{BESS}(t)| \pm \beta^{TOU}(t) \times P^{BESS}(t) \rightarrow \forall t \in T \tag{3.34}$$

$$A_{BESS} = \frac{COST^{BESS}_{capital} \times P^{BESS}_{capital} \times AIR}{T_{life} \times 365 \times 24 \times CF_{BESS}}; \rightarrow B_{BESS} = COST^{O\&M}_{BESS} \tag{3.35}$$

$$\begin{cases} COST^{\varsigma} = COST^{\varsigma}_{O\&M}(t) + H_{\varsigma} \times COST^{\varsigma}_{EMI}(t) \\ COST^{\varsigma}_{O\&M}(t) = c + b \times P_{\varsigma}(t) + a \times P^2_{\varsigma}(t) \quad \rightarrow \forall \varsigma \in \\ COST^{\varsigma}_{EMI}(t) = \left(C^{\varsigma}_{CO_2} + C^{\varsigma}_{SO_2} + C^{\varsigma}_{NO_2}\right) \times P_{\varsigma}(t) \end{cases}$$

$$\{DiselGenerator, Grid\}, \forall t \in T \tag{3.36}$$

$$H_{\varsigma} = \frac{COST^{\varsigma}_{O\&M}(t)}{COST^{\varsigma}_{EMI}(t)}\Bigg| P^{MAX}_{\varsigma} \rightarrow \forall \varsigma \in \{DiselGenerator, Grid\}, \forall t \in T \tag{3.37}$$

Where, A_{ς} is Capital cost component. The $COST^{\varsigma}_{capital}$ is the initial investment in the system. B_{ς} is operational and Maintenance (O&M) cost component. $COST^{O\&M}_{\varsigma}$ are ongoing costs for running and maintaining the system. $COST^{\varsigma}_{EMI}$ is Emission cost. H_{ς} is emission factor.

3.7. MODELING UNCERTAINTY

The unpredictable characteristics of wind power generation and photovoltaic systems present a challenge in MG operation. Neglecting uncertainty issues leads to unrealistic and inaccurate model results. To address this, a stochastic model based on scenario generation and reduction has been employed to improve the module's reliability and mitigate uncertainties associated with PV and WT. The uncertainty associated with solar radiation is typically addressed by fitting its probability distribution using the beta Probability Distribution Function (PDF):

$$PDF(x) = \frac{\wp(\alpha+\beta)}{\wp(\alpha)+\wp(\beta)} \times x^{\alpha-1} \times (1-x)^{\beta-1} \tag{3.38}$$

Where, α and β are determined from the mean value ϑ, and the standard deviation using equation (3.39).

$$\beta = (1-\vartheta) \times \left(\frac{\vartheta(1-\vartheta)}{\delta^2} - 1\right),\ \alpha = \frac{\vartheta \times \beta}{1-\vartheta} \tag{3.39}$$

Additionally, the uncertain behavior of wind is commonly described using the Weibull distribution function. Further details regarding modelling and parameter selection are available in [96].

$$PDF(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{\beta-1} exp(-\left(\frac{v}{c}\right)^{k}) \Rightarrow k = \left(\frac{\delta}{c}\right)^{k};\ c = \frac{\vartheta}{\wp(1+\frac{1}{k})} \tag{3.40}$$

Where, k and c represent the shape and scale parameters for the Weibull function, respectively.

After generating scenarios, a backward scenario reduction technique is applied [96]. Initially, the interval for each pair of scenarios is calculated. Subsequently, for each scenario, the one with the shortest distance is determined. The closest match for each scenario is identified by multiplying the probability of scenarios occurring at the distance of the scenario's closest match. The scenario with the least impact is identified and eliminated.

3.8. SUMMARY

The overall structure of the studied system, the proposed framework, and the implementation procedures are described in this chapter. First, the modelling of the main components of the MG—including DGs, loads, and inverters—is presented. Then, the control algorithms and coordination strategies used to manage the system operation under different scenarios are given. The technical background needed to evaluate the system performance in the next chapter is established in this chapter.

PART 4

RESULTS AND DISCUSSIONS

In this chapter, the results of the simulation of the proposed framework strategies are presented and analysed. The performance of PNLMPC is evaluated under various operating conditions .the PNLMPC is simulated by MATLAB 2023a. The simulation employs the NLMPC toolbox provided by MATLAB Simulink on a PC running Windows 10 Pro, equipped with an Intel Corei7-6500U processor clocked at 2.50 GHz and 12.0 GB of RAM.

4.1. INPUT PARAMETERS OF THE SYSTEM

Figures 4.1, 4.2, and 4.3 illustrate the uncertainties associated with wind speed, solar radiation, and ambient temperature, respectively. These uncertainties are modelled using PDF to accurately capture the variability in these parameters.

Fluctuations in wind and solar power caused by weather uncertainties can significantly affect the stability and reliability of both grid-connected and islanded MGs. These variations in power generation may lead to voltage and frequency instability, complicating load management. Additionally, uncertainties in ambient temperature can influence the efficiency and output of generating units. To address these challenges, the MG design should integrate energy storage solutions, such as batteries, to mitigate the variability in renewable power generation. Furthermore, the control and energy management system must be designed to accommodate the dynamic nature of renewable energy production and ensure stable operation of the MG.

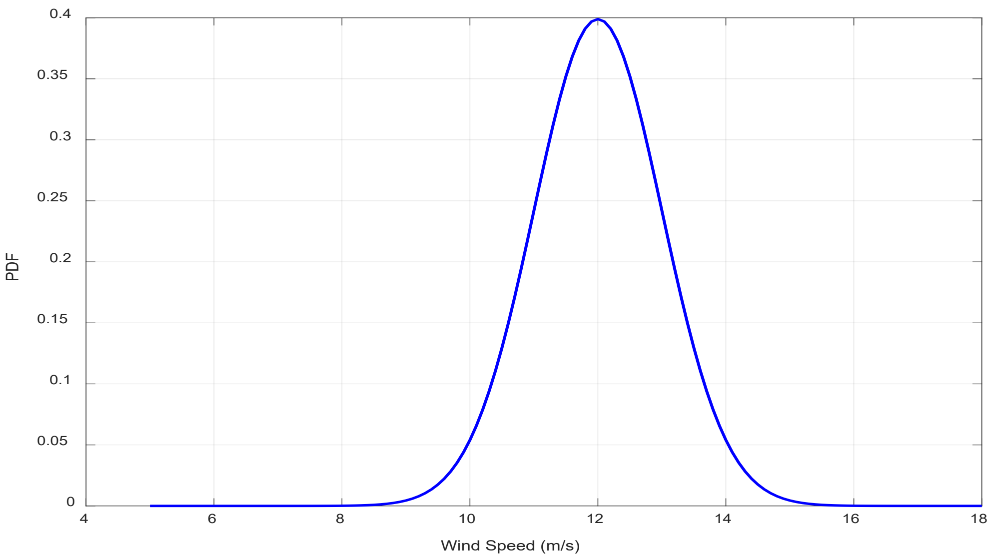


Figure 4.1. The PDF of nominal wind speed variations during operation of MG

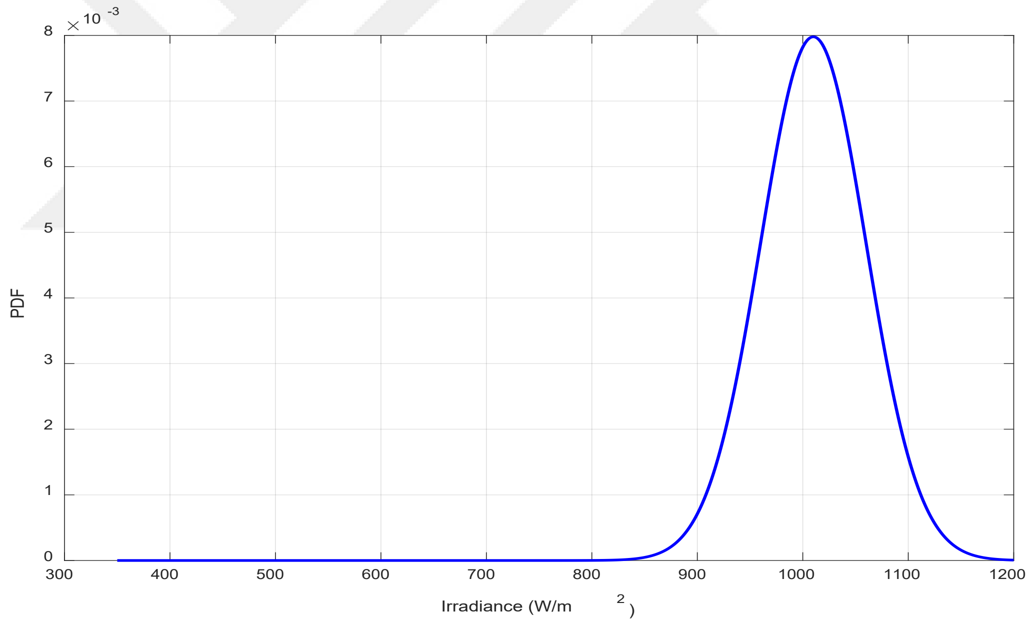


Figure 4.2. The PDF of nominal Irradiance variations during operation of MG

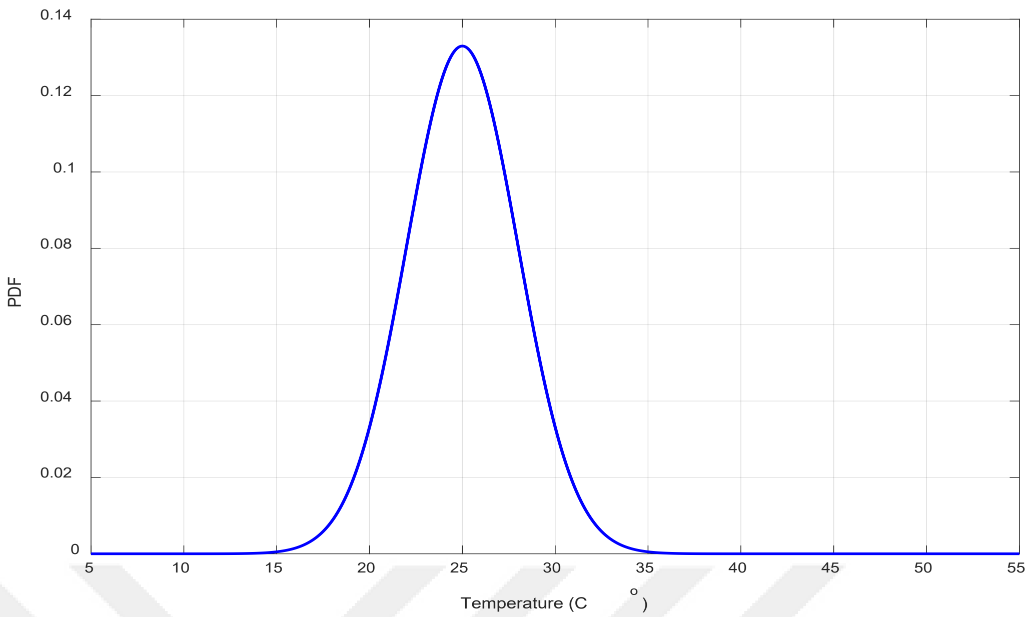


Figure 4.3. The PDF of nominal temperature variations during operation of MG.

Moreover, loads within a MG exhibit variability and uncertainties due to factors such as changes in consumer behavior, weather conditions, and fluctuations in load demand. Figures 4.4 and 4.5 illustrate these uncertainties in both active and reactive loads, simulated using PDF. The peaks of the PDF curves represent the load magnitudes with the highest probability of occurrence during MG operation. This information is crucial for understanding the dynamic behavior of the MG and its response to load changes. Insights from Figures 4.4 and 4.5 can inform the design and operation of the MG, including ESS sizing, optimization of control strategies, and evaluation of system stability and resilience.

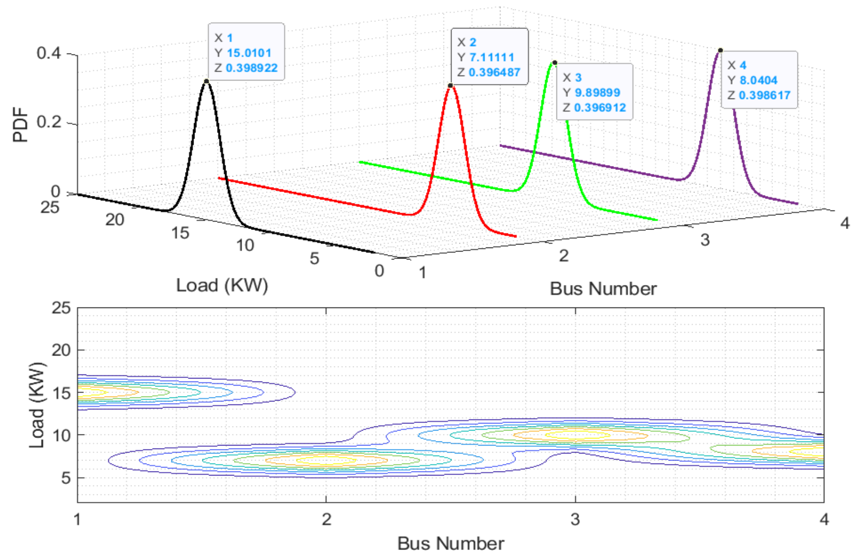


Figure 4.4. The PDF of nominal active load variations during operation of MG.

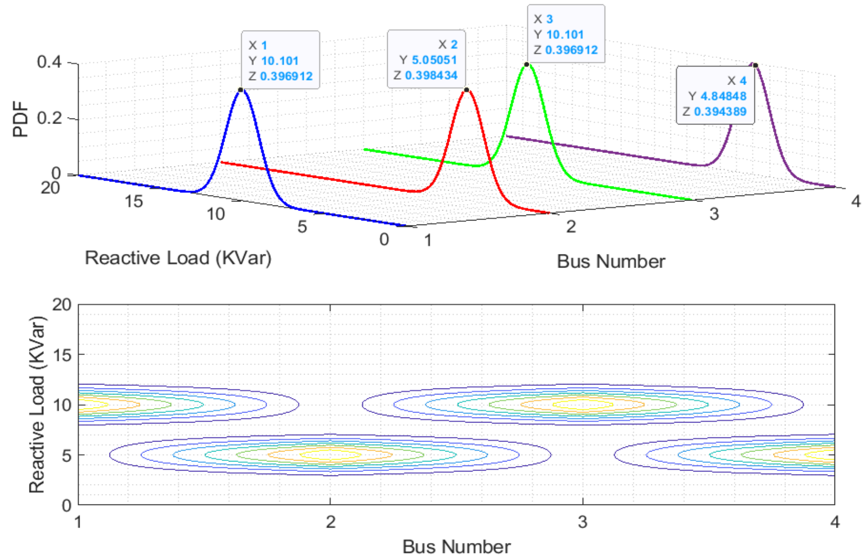


Figure 4.5. The PDF of nominal reactive load variations during operation of MG.

4.2. RESULTS AND ANALYSIS

This section is divided into two parts to analyse the islanded MG and the grid-connected MG separately.

4.2.1. Results and Analysis of Islanded Microgrid

Figures 4.6 and 4.7 depict a continuous-time representation of active and reactive power. In Figure 4.6, the green line represents the active power reference, while the purple line illustrates the combined active power generated from all MG DGs. Notably, at the 15th second, the active power dynamically transitions from 40 kW to 130 kW. The PNLMPC adjusts the DGs to ensure that the summation of generated active powers closely follows the active power reference with high accuracy and speed. This results in a balanced relationship, where the sum of generated active power corresponds to the sum of active power consumption.

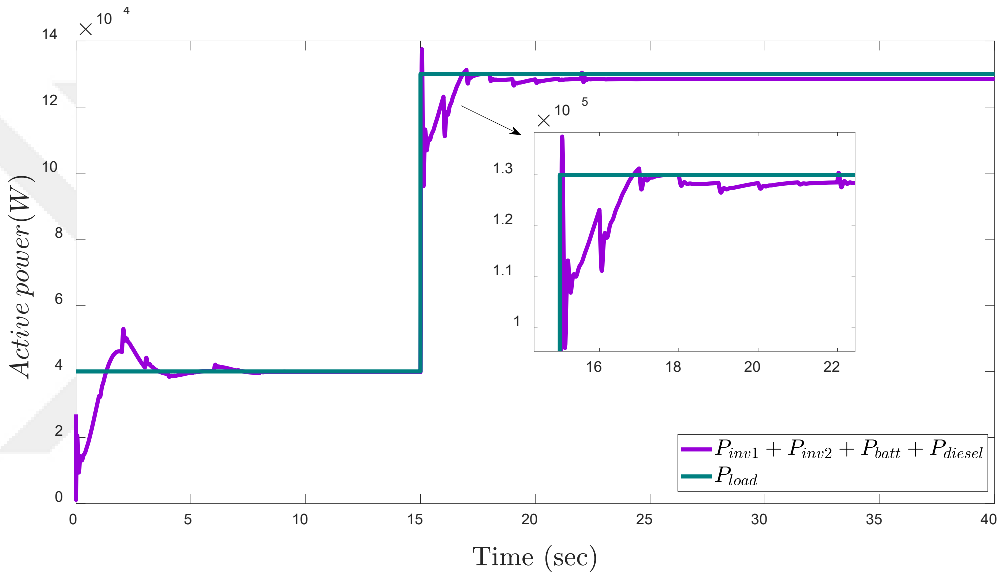


Figure 4.6. Active power dynamics in the islanded MG, regulated for balance by PNLMPC.

Furthermore, in Figure 4.7, the reactive power reference is denoted by the pink line, and the blue line represents the summation of generated reactive power from all DGs in the MG. Significantly, at the 22nd second, the reactive power dynamically shifts from 30 kVAR to 40 kVAR. The NLMPC regulates the DGs to guarantee that the total generated reactive power closely tracks the reactive power reference with precision and speed. This leads to an equilibrium where the total amount of generated reactive power corresponds with the total amount of reactive power consumption.

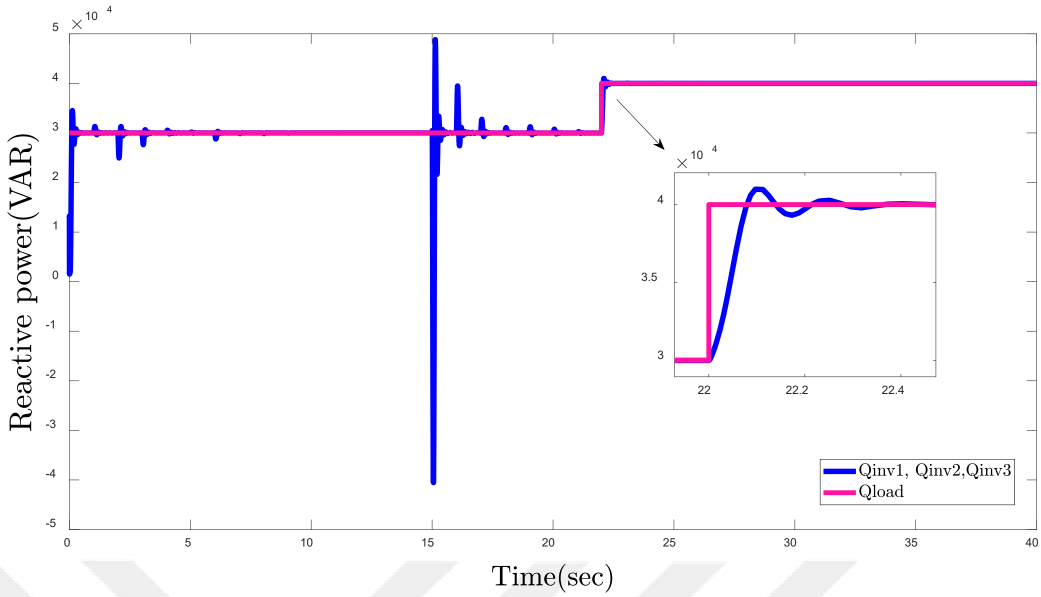


Figure 4.7. Reactive power dynamics in the islanded MG, regulated for balance by PNLMPC.

Figures 4.8 to figure 4.11 provide a detailed insight into the optimal output of active power from individual DGs within the MG. The PV panel and wind turbine showcase their optimal generation in green and purple, respectively, while the diesel generator and battery storage indicate their optimal active power generating rates in grey (figure 4.10) and red (Figure 4.11).

Figure 4.11 specifically highlights the active power generated by the battery storage system. Initially, negative active power during the first 10 seconds signifies the battery being in a charging state. Once reaching full charge, the battery ceased to receive power input from the 10th to the 15th second. However, a substantial surge in active power consumption, from 40 kW to 130 kW at the 15th second, triggered the battery to commence discharging, exhausting its stored energy by the 20th second. Consequently, by the 25th second, the battery ceased supplying any additional active power to the MG. In the event of the battery being unable to provide active power to the MG, inverters 1 and 2 sequentially intervene to compensate, as depicted in Figures 14 and 15. Particularly noteworthy is , initiating an escalation in active power production to regulate voltage and frequency. This compensation mechanism ensures a delicate balance between total active power consumption and generation, as demonstrated in Figure 4.9. Commencing from the 20th second onwards, there's a concerted effort towards both voltage and frequency control, coupled with optimizing the economic efficiency of the MG to maintain network stability.

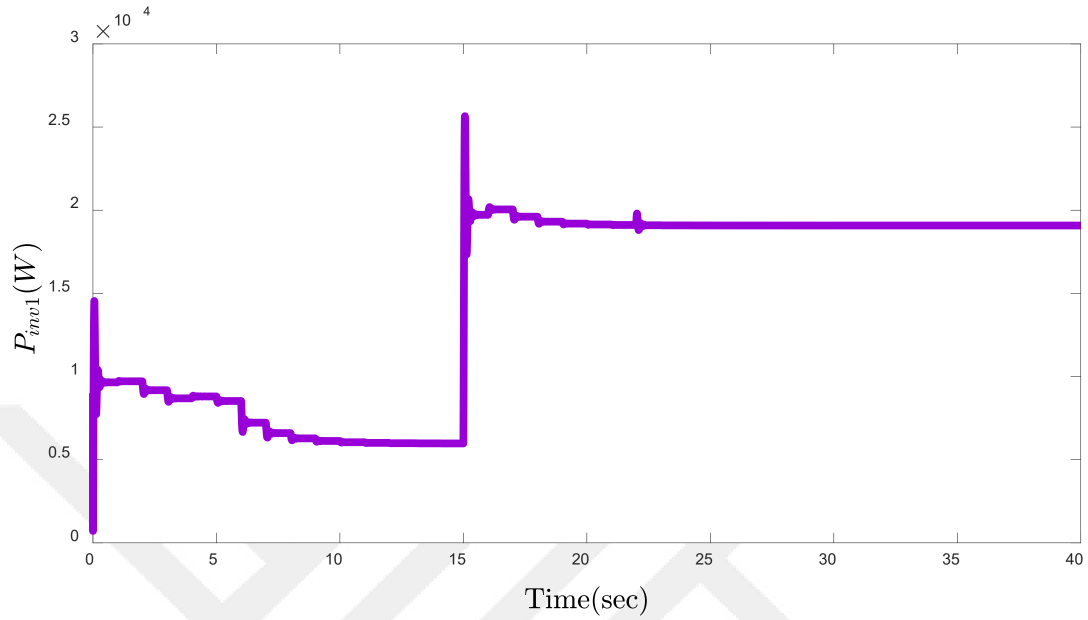


Figure 4.8. Peak of active power generation from PV panels, in islanded MG.

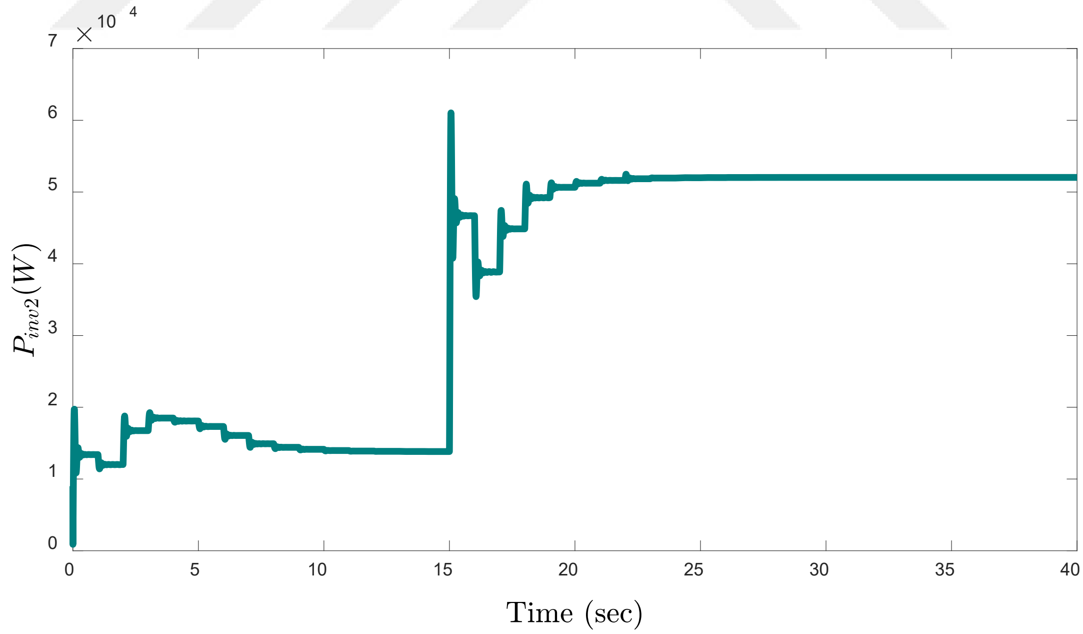


Figure 4.9. Peak of active power generation from wind turbine, in islanded MG.

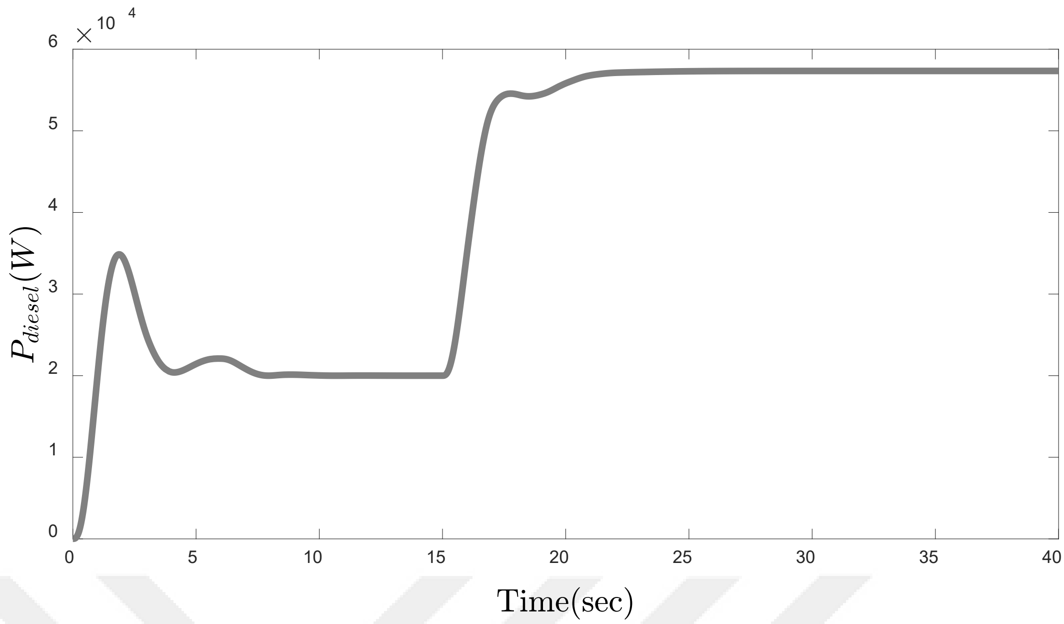


Figure 4.10. Peak active power generation from diesel generator, in islanded MG.

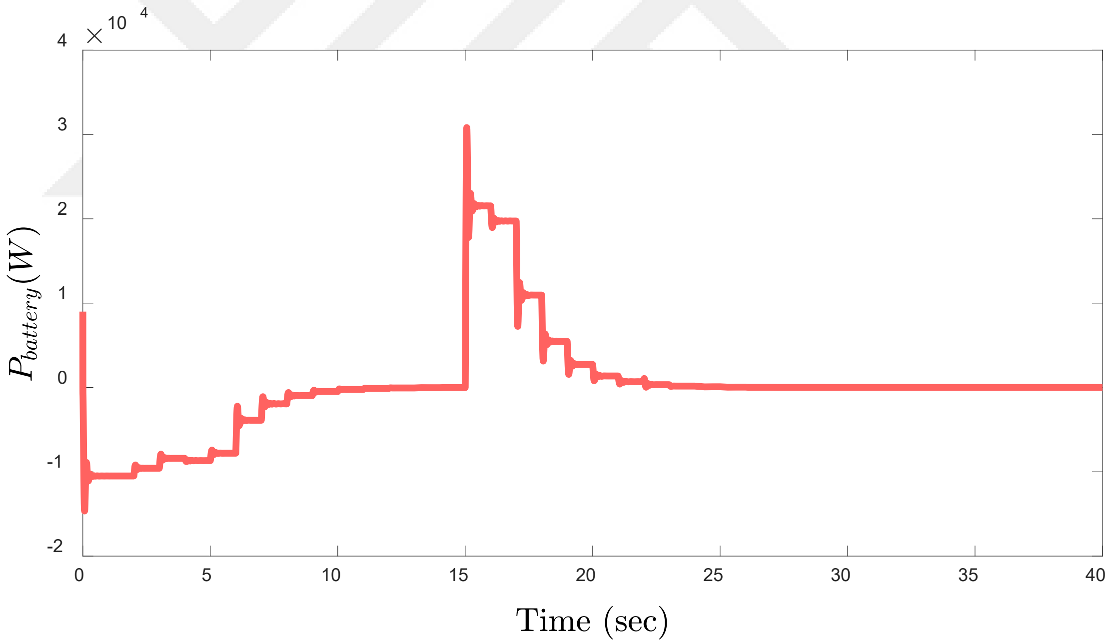


Figure 4.11. Peak active power generation from battery storage, in islanded MG.

Figure 4.12 provides an overview of the battery storage status managed by PNLMPC, initially charged to 20 Wh (equivalent to 25% State of Charge). The battery's protective range is set between 100% and 25%. As shown in Figure 4.11, during the initial 15 seconds, with low active power, the battery underwent a steady charging process, reaching full capacity at 100% or 80 Wh. However, at the 15th second, with a sharp increase in active power from 40 kW to 130 kW, the battery discharged to support the MG, reaching a discharge level of 25%. This discharge strategy ensures the protection of the storage device, preventing deep discharge as per the limitations of the protection system.

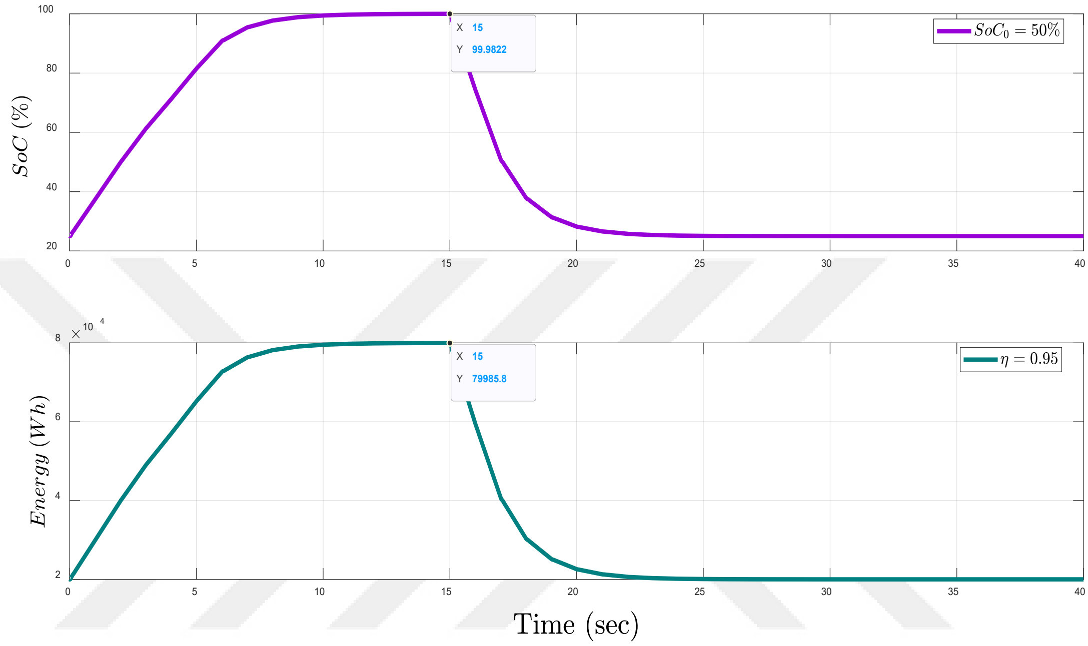


Figure 4.12. PNLMPC -managed battery storage dynamics.

Frequency characteristics (in rad/sec) of inverters 1, 2, and the BESS are displayed in Figure 4.13. These results unequivocally showcase the efficacy of our proposed method in consistently upholding stable frequency levels, even amidst fluctuations in both active and reactive power.

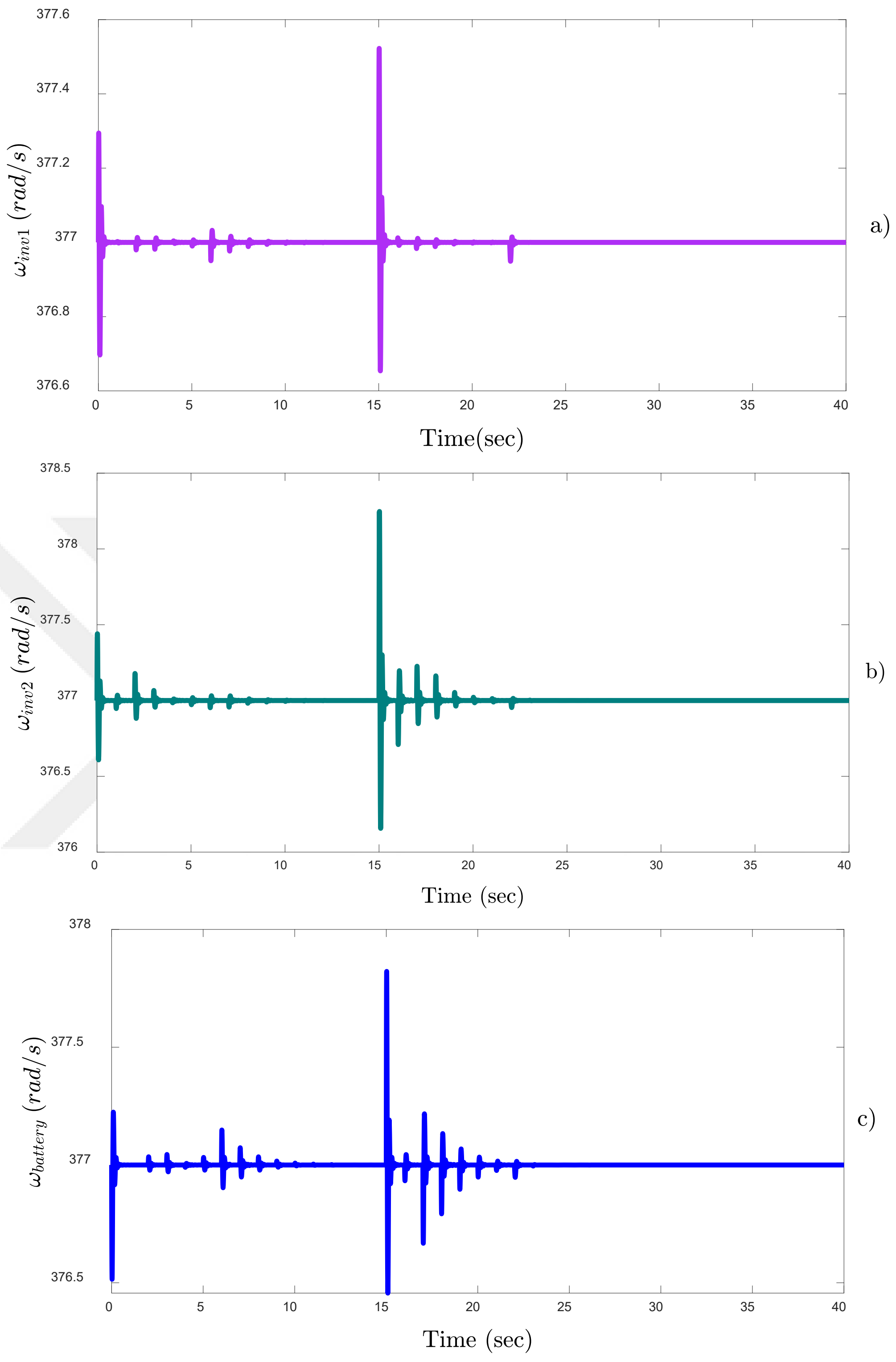


Figure 4.13. Stable frequency control amidst power fluctuations with PNLMPC in islanded MG. a) controlling the frequency of photovoltaic systems (inverter 1). b) controlling the frequency of wind turbine (inverter 2). c) controlling the frequency of BESS (inverter 3)

4.2.2. Performance Comparison in Islanded Microgrid

Figure 4.14 presents a comparative analysis examining voltage performance across different control methods. Specifically, three distinct controllers are evaluated for voltage stability: the PNLMPC, depicted by a black line; a standard MPC, represented by a blue line; and an adaptive MPC, illustrated with a red line. The voltage level is standardized at 380 V in this experimental setup. It's evident that the PNLMPC exhibits superior control before any significant changes. Moreover, at the 15th (Sec) time interval, amidst an escalation in active power demand, the PNLMPC, indicated by the black line, demonstrates the most effective voltage regulation during this period. Furthermore, it swiftly converges to the reference value after that, while the remaining controllers fail to track the reference closely. Notably, the voltage fluctuates between 381.6 V and 382.2 v before and after the fluctuation in the PNLMPC. At the same time, the range for the adaptive MPC spans from 383.5 V to 387.7 V, and the reference targets cannot be met. Similarly, the standard MPC struggles to adhere to the references, registering 385.5 v before the fluctuation and reaching 396.6 V post-fluctuation.

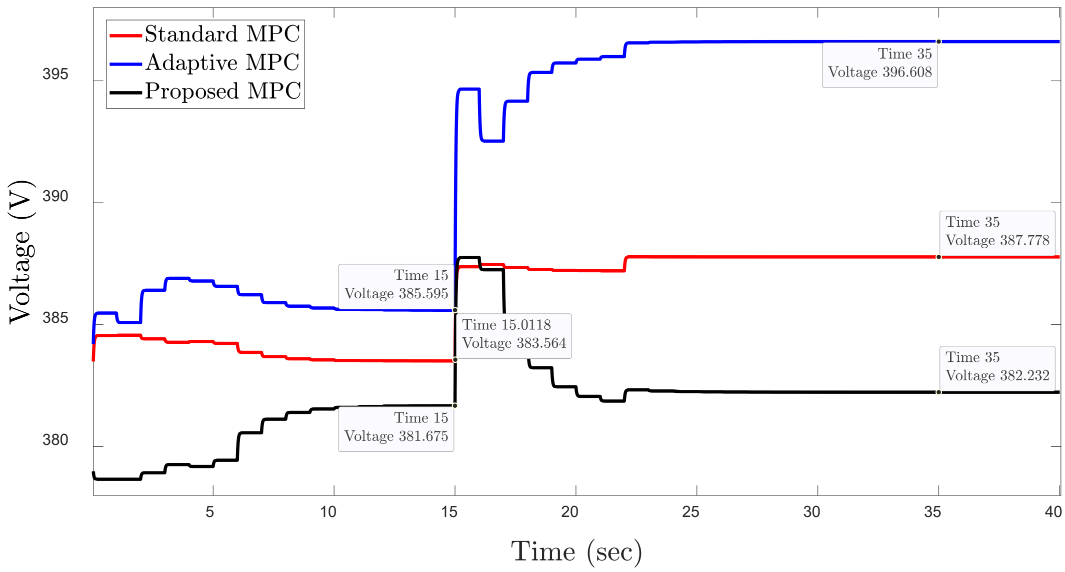


Figure 4.14. Comparative analysis of voltage stability across PNLMPC, Standard MPC, and Adaptive MPC.

Moreover, optimization extends beyond technical parameters to encompass economic considerations for validation during the operational phase. Hence, the PNLMPC controller is tasked with adjusting generation to minimize all operational costs arising from sudden changes. In Figure 4.15, three different controllers are analysed: the PNLMPC (depicted by the black line), the standard MPC (shown in red), and the adaptive MPC (represented by the blue line). Before any shifts in active power, costs are uniform across all controllers. However, at the 15th moment, when a sudden load increase occurs, the PNLMPC swiftly adapts generation to minimize operational costs, displaying superior speed and accuracy compared to its counterparts. Additionally, as evident from the magnified section of Figure 4.15, the PNLMPC consistently causes lower costs throughout the system's startup phase than alternative controllers. Following load increases and stabilization of inverters, the PNLMPC system continually adjusts distributed generation capacity to minimize operational expenses. Given the significant load increase at the 15th moment, the discrepancy in operational costs becomes more pronounced.

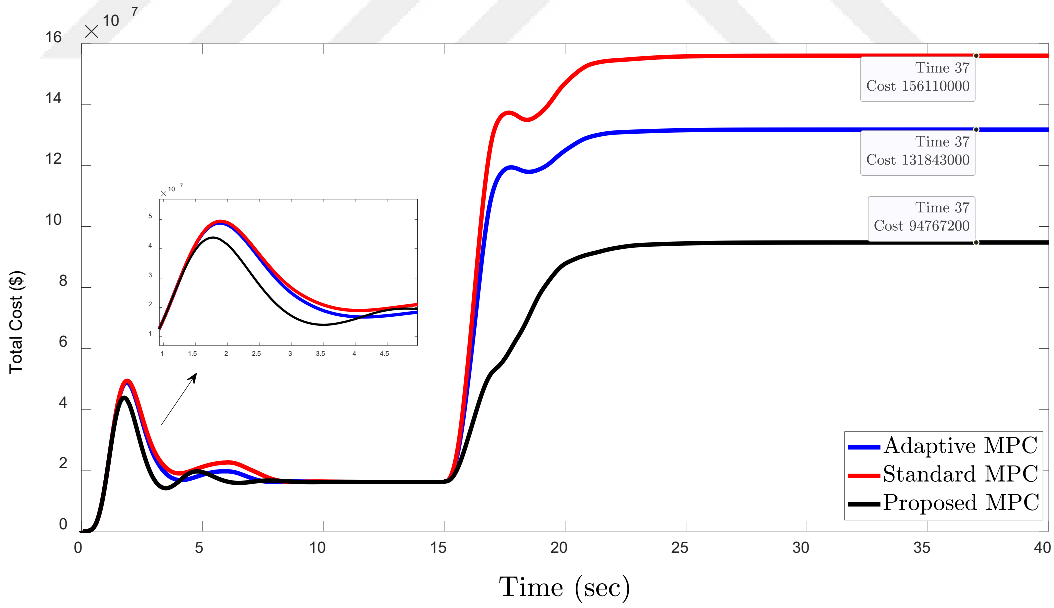


Figure 4.15. Comparative analysis of economic parameter optimization for PNLMPC, Standard MPC, and Adaptive MPC.

Table 4.1 has been compiled for a comparative analysis between PNLMPC and alternative methodologies as part of our validation efforts. The results of optimizing the objective function using PNLMPC and other methods are presented. The proposed optimization algorithm consistently outperforms its counterparts across all metrics, demonstrating superior performance. To ensure fairness, the results from other methodologies were implemented by us, using the same objective function and parameters as in the original papers. A fixed number of problem evaluations were allocated to all methods to ensure a meaningful comparison and control for computational cost differences. All methodologies addressed the same optimization problem, enabling a direct assessment of PNLMPC's performance. This systematic evaluation aimed to discern each method's relative strengths and weaknesses, providing valuable insights into their practical applicability for the same task.

Table 4.1. Comparative analysis between PNLMPC and alternative methodologies for validation.

Consideration Statues	**Operating Cost($)**	**Total Voltage Deviation (%)**	**Frequency Deviation (%)**	**CPU-Time for 40(sec) Simulation**
PNLMPC	94767200	0.26	0.00045	39.4
Standard MPC [163, 164]	156110000	1.84	0.0832	600
Adaptive MPC [165, 166]	131843000	4.2	0.0173	1125

Table 4.1 clearly illustrates that the difference in cost savings between the Standard MPC and Adaptive MPC is around 15.54%. Additionally, the PNLMPC reduced costs by 39.29% compared to the Standard MPC and by 28.12% compared to the Adaptive MPC. Furthermore, PNLMPC shows significantly lower total voltage deviation and frequency deviation compared to both Standard MPC and Adaptive MPC, with values of 0.26% and 0.00045%, respectively. In terms of total voltage deviation, PNLMPC achieves an outstanding reduction of 85.87% and 87.62% compared to Standard MPC and Adaptive MPC, respectively. Similarly, PNLMPC demonstrates remarkable improvements of 99.46% and 96.62% in frequency deviation compared to Standard MPC and Adaptive MPC, respectively. Additionally, PNLMPC demonstrates the shortest CPU-Time for 40 seconds of simulation, showcasing its efficiency in convergence and calculation, thus highlighting the effectiveness of the proposed framework in real-time applications.

4.2.3. Results and Analysis of Grid-Connected Microgrid

Figures 4.16 and 1.17 depict a continuous-time representation of active and reactive power. In Figure 4.16, the green line represents the active power reference, while the orange line illustrates the combined active power generated from all MG DGs. Notably, at the 15th second, the active power dynamically transitions from 40 kW to 130 kW. The PNLMPC adjusts the DGs to ensure that the summation of generated active powers closely follows the active power reference with high accuracy and speed. This results in a balanced relationship, where the sum of generated active power corresponds to the sum of active power consumption.

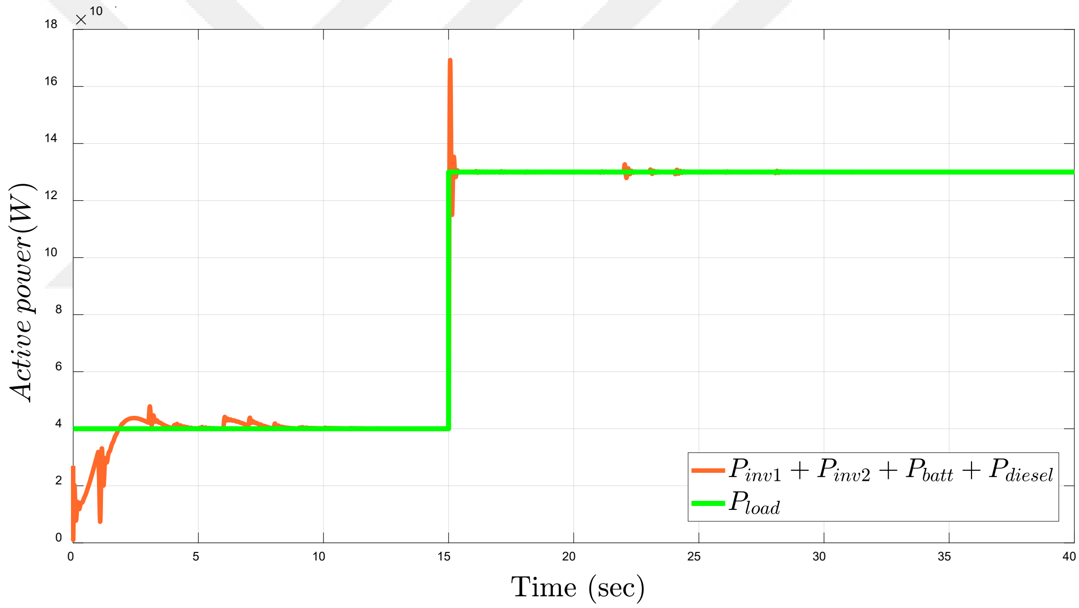


Figure 4.16. Active power dynamics in the grid-connected MG, regulated for balance by PNLMPC.

Furthermore, in Figure 4.17, the reactive power reference is denoted by the pink line, and the purpule line represents the summation of generated reactive power from all DGs in the MG. Significantly, at the 22nd second, the reactive power dynamically shifts from 30 kVAR to 40 kVAR. The NLMPC regulates the DGs to guarantee that the total generated reactive power closely tracks the reactive power reference with precision and speed. This leads to an equilibrium where the total amount of generated reactive power corresponds with the total amount of reactive power consumption.

Given that there are four degrees of freedom for active power control—namely Inverter 1, Inverter 2, Inverter 3, and the Diesel Generator—managing active power under normal operating conditions or gradual changes is relatively straightforward. Each inverter can adjust its output to maintain the desired active power level, and the Diesel Generator provides additional support when needed. However, the situation becomes more complex when, at second 22, there is a disturbance causing an increase in reactive power. In this scenario, controlling reactive power becomes more challenging because the degrees of freedom for reactive power control are reduced to three variables (Inverter 1, Inverter 2, and Inverter 3), and the Diesel Generator, which would typically offer further control, is no longer available to assist in regulating the system.

At second 15, the system encounters a sudden increase in active power, which managing is one of the key objectives in this thesis. The system tries to stabilize active power as quickly as possible, which may result in minor fluctuations in reactive power. These fluctuations are not significant enough to disrupt the overall system performance, as our proposed framework is designed with real-world conditions in mind and has a practical operational behavior. Thus, a sudden drop in reactive power occurs but is quickly compensated for, taking less than 0.05 seconds. This system behavior demonstrates its flexibility and capability in handling various real-world scenarios, as the control strategy has accounted for all realistic conditions and possibilities.

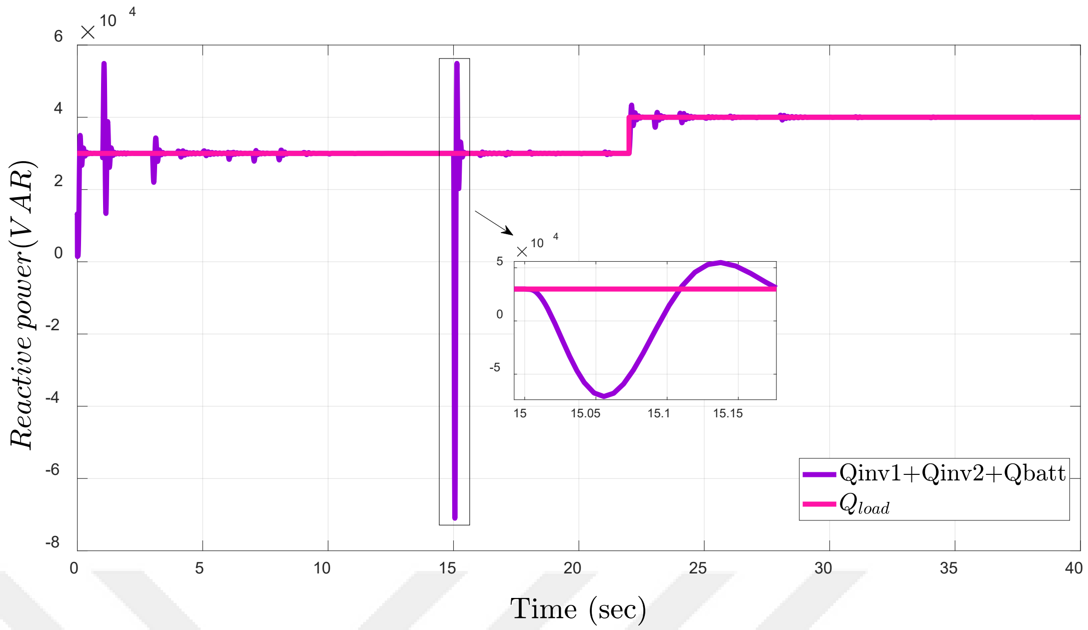


Figure 4.17. Reactive power dynamics in the grid-connected MG, regulated for balance by PNLMPC.

Figures 4.18 through 4.21 offer a comprehensive view of the optimal active power output from individual DGs within the MG. The Utility and PV panel display their optimal generation capacities in orange and green, respectively. Meanwhile, the diesel generator's optimal active power generation is highlighted in yellow (Figure 4.20), and the battery storage system is shown in blue (Figure 4.21).

Figure 4.21 provides a closer look at the behavior of the battery storage system. Initially, during the first 10 seconds, the battery is in a charging state, as indicated by the negative active power output. From the 10th to the 15th second, the battery reaches full charge and halts further power intake. However, at the 15th second, a significant increase in load demand—from 40 kW to 130 kW—causes the battery to shift into discharging mode, rapidly depleting its stored energy by the 20th second. Following this, until the 22nd second, the battery resumes discharging to provide reactive power to the system, as it becomes more economical than sourcing this power from the utility grid. After contributing reactive power, the battery stops supplying any active power to the MG by the 30th second.

In scenarios where the battery is unable to supply sufficient active power, Inverters 1 and 2 step in to stabilize the system, as shown in Figures 4.18 and 4.19. In these instances, the inverters increase their active power generation to compensate for the shortfall, ensuring voltage and frequency regulation. This compensation mechanism plays a crucial role in maintaining the balance between total active power consumption and generation, as evidenced by Figure 4.19. Starting from the 20th second, the system shifts focus towards controlling voltage and frequency, while simultaneously optimizing the MG's economic performance to uphold overall network stability.

This coordinated effort among the utility, PV system, diesel generator, and battery storage ensures that the network operates efficiently, even during fluctuating load conditions, while minimizing operational costs and preserving system reliability.

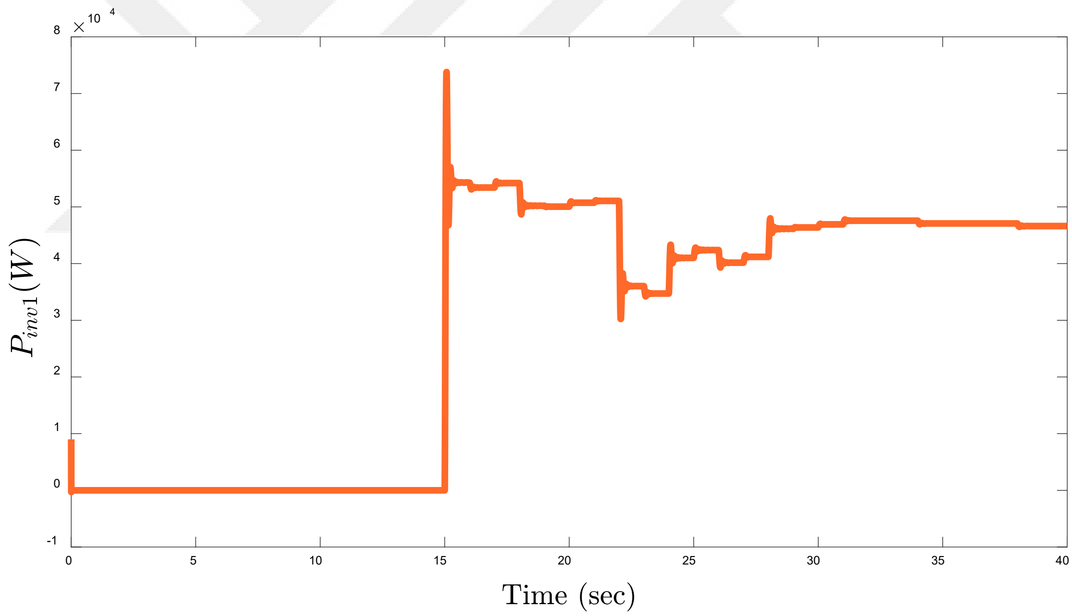


Figure 4.18. Peak of active power generation from Utility, in grid-connected MG.

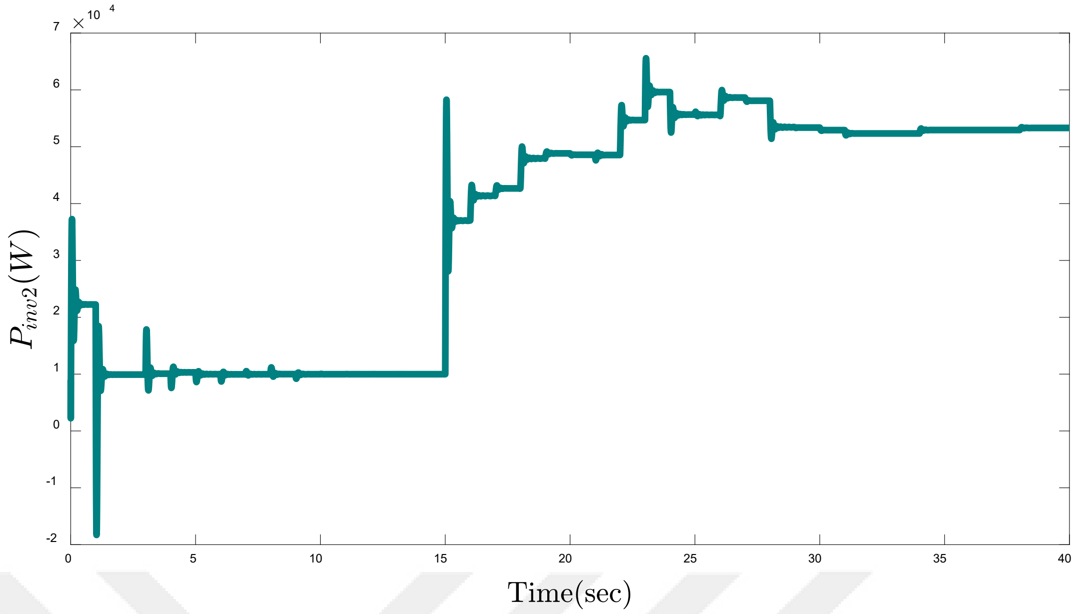


Figure 4.19. Peak of active power generation from PV panels, in grid-connected MG.

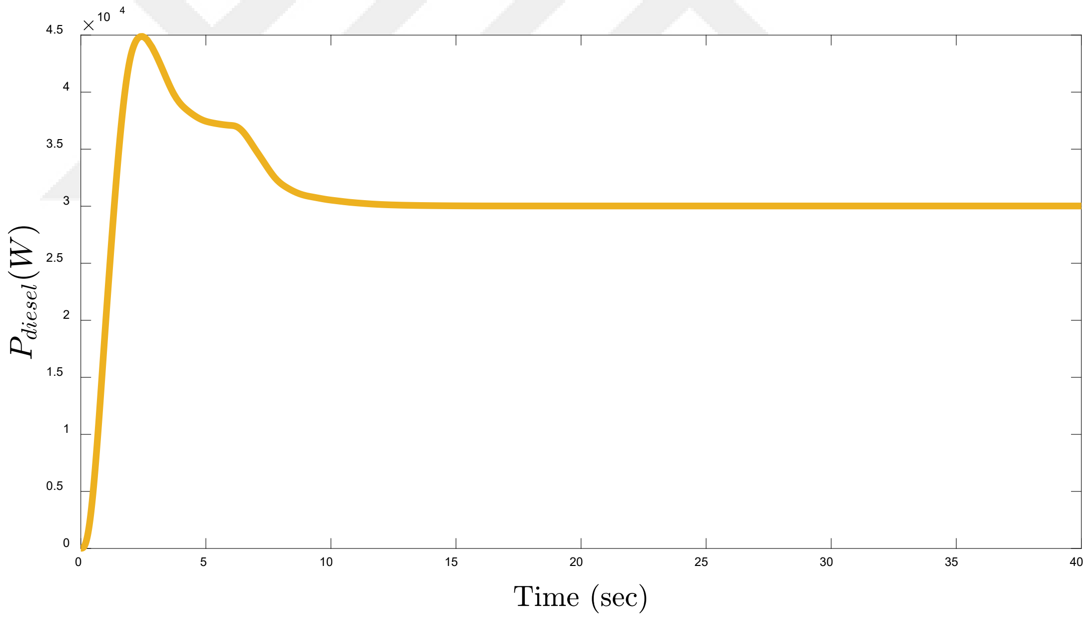


Figure 4.20. Peak of active power generation from diesel generator, in grid-connected MG.

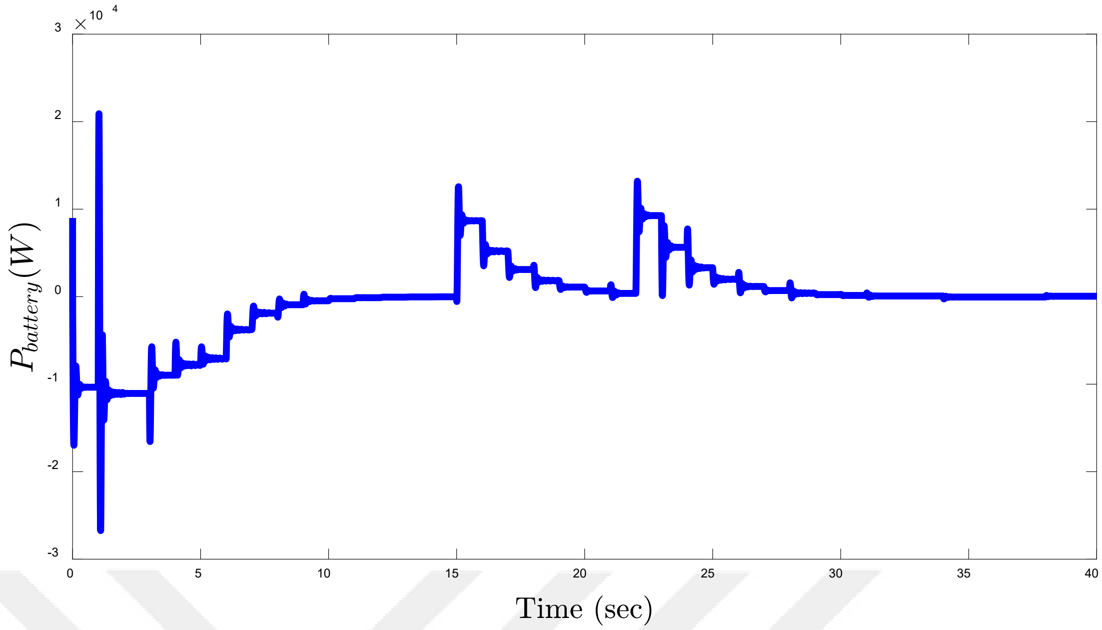


Figure 4.21. Peak of active power generation from battery storage, in grid-connected MG.

As illustrated in Figure 4.22, at 15 seconds, the system encounters an increase in active power demand, prompting the battery to begin discharging gradually. When the demand for reactive power sharply rises in 22 seconds, the battery discharges more rapidly to reduce overall operational costs. However, by the 30th second, the cost of sourcing power from the utility becomes lower than that of the battery. As a result, the PNLMPC system halts the battery discharge, preventing further contribution from the battery to the system, thereby optimizing cost-efficiency.

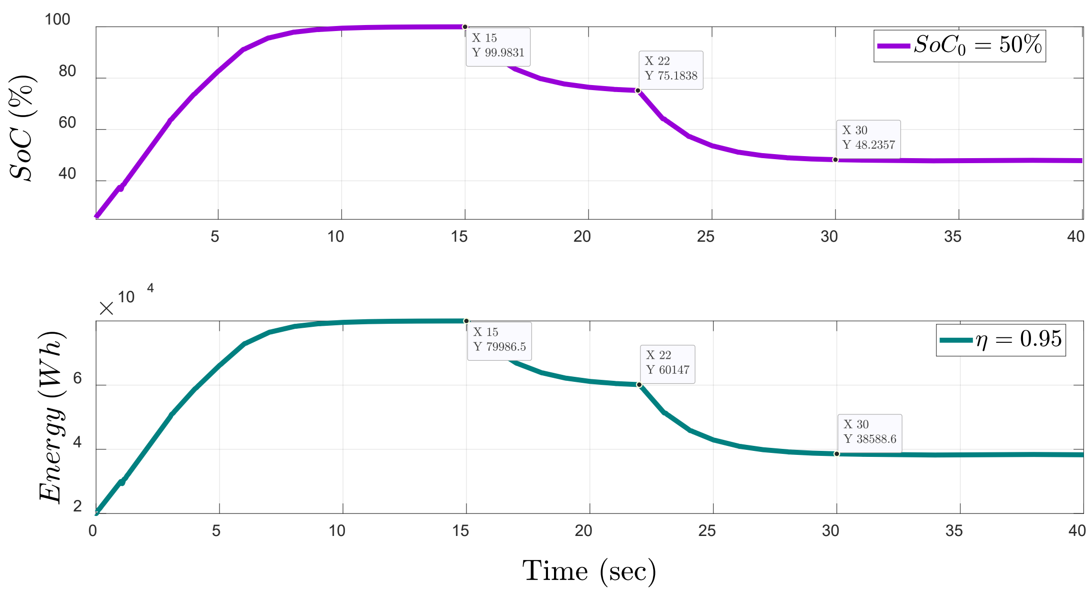
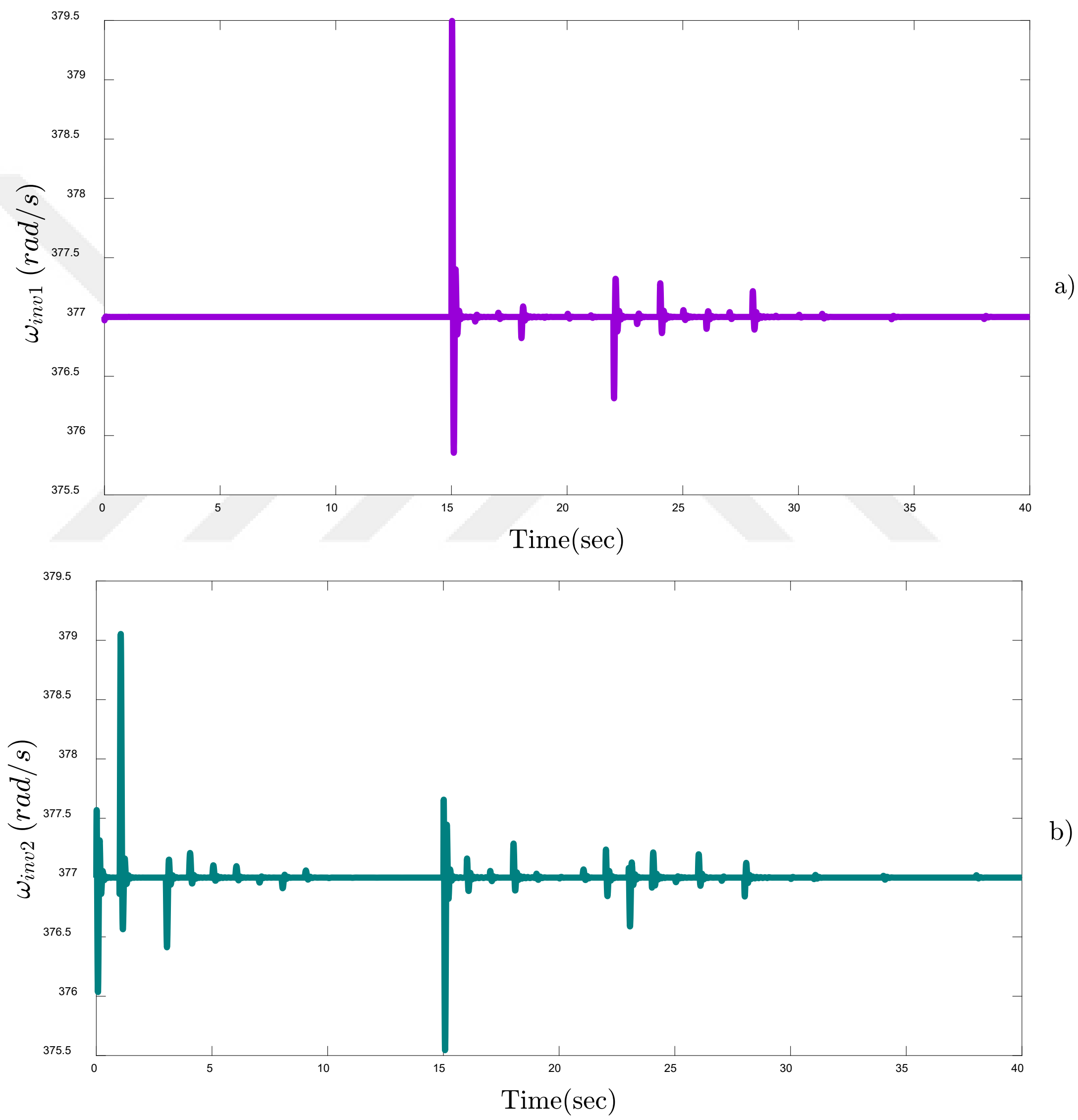


Figure 4.22. PNLMPC -managed battery storage dynamics.

Frequency characteristics (in rad/sec) of inverters 1, 2, and the BESS are displayed in Figure 4.23. These results unequivocally showcase the efficacy of our proposed method in consistently upholding stable frequency levels, even amidst fluctuations in both active and reactive power.



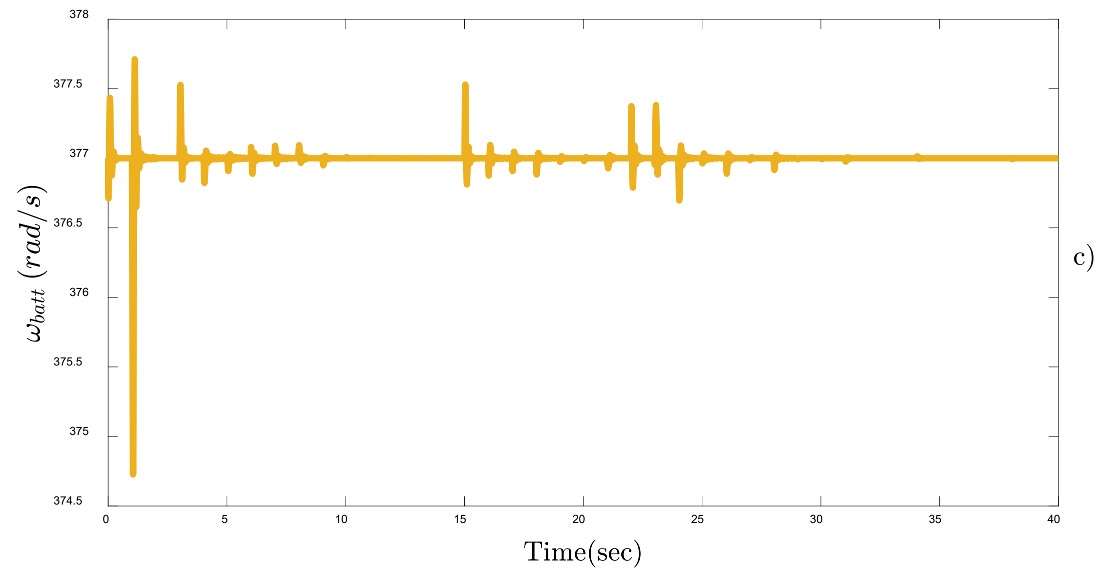


Figure 4.23. Stable frequency control amidst power fluctuations with PNLMPC in gid-connected MG. a) controlling the frequency of Utility (inverter 1). b) controlling the frequency of photovoltaic systems (inverter 2). c) controlling the frequency of BESS (inverter3)

4.2.4. Performance Comparison Grid-Connected Microgrid

Figure 4.24 provides a comparative analysis of voltage performance across different control methods. The study evaluates three controllers for voltage stability: PNLMPC (black line), standard MPC (blue line), and adaptive MPC (red line). The voltage is standardized at 380 V for this experiment. The results highlight that the PNLMPC delivers the most effective control prior to significant changes. At the 15th-second, when active power demand increases, the PNLMPC (black line) demonstrates the best voltage regulation, maintaining a stable voltage of 385 V both before and after the fluctuation. In contrast, the adaptive MPC fluctuates between 388 V and 399 V, failing to meet the reference targets. Similarly, the standard MPC struggles to maintain voltage stability, dropping to 364.2 V before the fluctuation and rising to 399 V after it.

In Figure 4.24, the PNLMPC demonstrates significantly better performance compared to the Adaptive and Standard MPC techniques. Specifically, PNLMPC achieves a 37.5% improvement over Adaptive MPC, illustrating greater adaptability and effectiveness in dynamic situations. Additionally, PNLMPC outperforms Standard

MPC by up to 73.68%, highlighting its potential for optimizing control processes, reducing errors, and enhancing overall system stability. These results clearly underscore the efficiency of the proposed approach in providing more accurate and robust control for complex grid-connected MG environments.

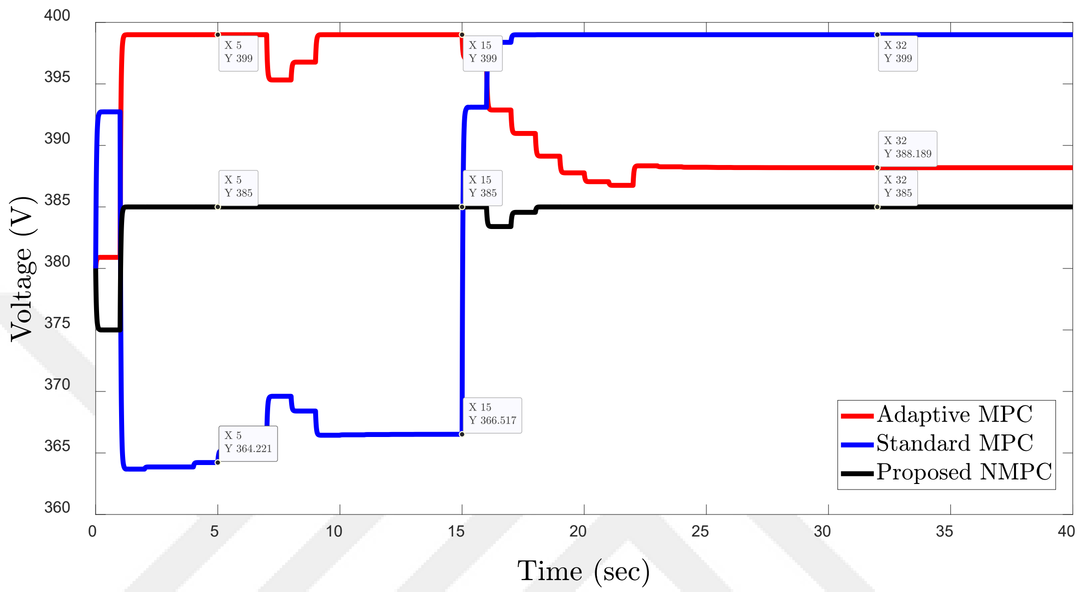


Figure 4.24. Comparative analysis of voltage stability across PNLMPC, Standard MPC, and Adaptive MPC.

Moreover, optimization extends beyond technical parameters to encompass economic considerations for validation during the operational phase. Hence, the PNLMPC controller is tasked with adjusting generation to minimize all operational costs arising from sudden changes. In Figure 4.25, three different controllers are analysed: the PNLMPC (depicted by the black line), the standard MPC (shown in red), and the adaptive MPC (represented by the blue line).

During the system's start-up phase, the PNLMPC continuously outperforms the alternatives in terms of cost efficiency. At the 15th second, when the network experiences a sudden surge in active power demand, the PNLMPC effectively maintains operational costs within the desired range, consistently delivering lower costs compared to other controllers.

As shown in the zoomed-in section of Figure 4.25, a slight increase in operational costs occurs across all controllers. However, after a few seconds, both the adaptive MPC and standard MPC struggle to control operational costs, leading to a gradual increase. By the 25th second, these controllers stabilize but at significantly higher cost levels. In contrast, the PNLMPC dynamically adjusts distributed generation capacity following the load increase and inverter stabilization, further minimizing operational expenses. As the load rises, the difference in operational costs becomes more pronounced, clearly showcasing the PNLMPC's superior cost efficiency. The PNLMPC significantly enhances cost reduction compared to both Adaptive and Standard MPC techniques. Specifically, it performs 35.83% better than Adaptive MPC, leading to a remarkable reduction in operational costs through the optimization of resource allocation and control strategies. Additionally, the PNLMPC outperforms Standard MPC by 24.19%, demonstrating its high efficiency in considering system dynamics to minimize costs. These results highlight the effectiveness of the PNLMPC in achieving cost savings while maintaining robust control, making it highly beneficial for complex and cost-sensitive applications such as MG management.

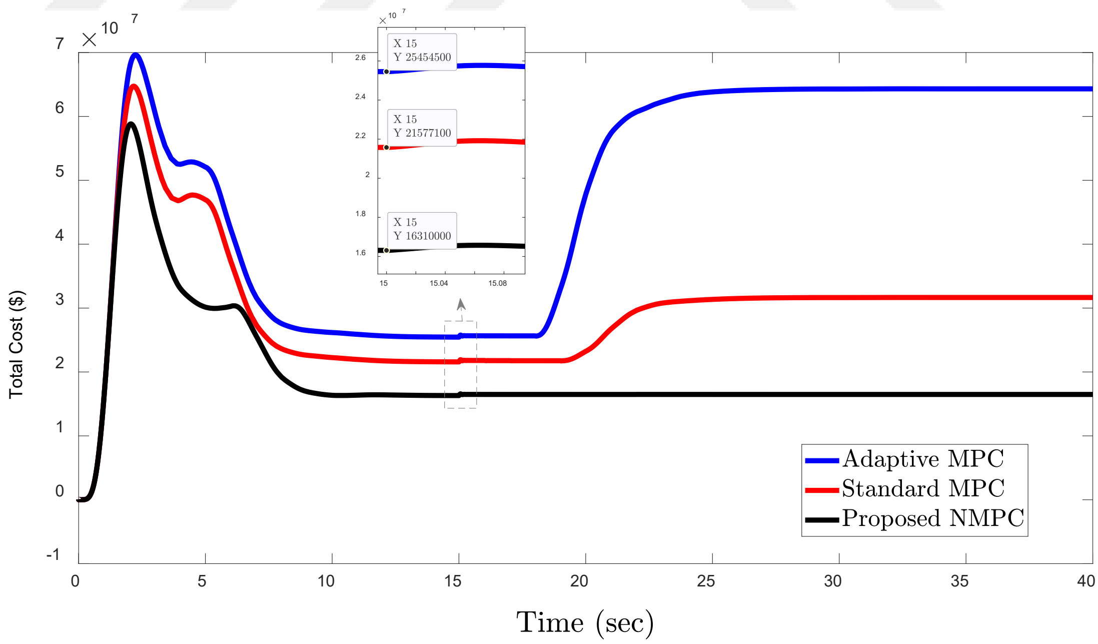


Figure 4.25. Comparative analysis of economic parameter optimization for PNLMPC, Standard MPC, and Adaptive MPC.

4.3. SUMMARY

In this chapter, simulation results for both modes of MG operation (the islanded and grid-connected) are examined. The results validate that the proposed framework performs quite well in coordinating the DGs and power sharing. The high performance is maintained even under conditions where the system is under extreme and abrupt changes in active power consumption and reactive power consumption.

PART 5

CONCLUSION AND FUTURE DIRECTION

This chapter provides a summary of this thesis and its achievements, along with suggestions for future direction in this field.

5.1. INTRODUCTION

Managing real-time control in MGs, particularly when considering the system's dynamics and components alongside a network preserving model (NPM), is a difficult undertaking that necessitates a combination of technical competence and economic understanding. This thesis proposes a new framework that incorporates NPM and continuous power flow (CPF) within an NLMPC to handle these challenges. Thus, the proposed strategy provides an efficient method for updating network parameters and managing resource generation, with the ultimate goal of fulfilling the system's real-time operational objectives. The study further highlights the consideration of inherent uncertainties within generation and consumption resources for realistic modelling of MG dynamics.

5.2. MAIN FINDING

This thesis has highlighted several primary findings:

5.2.1. Realistic Modelling of Microgrid Dynamics

By incorporating NPM into CPF, the proposed framework is allowed to represent the actual size of the complexity in MG dynamics: handling system uncertainties and performing optimizations for voltage-frequency regulation.

5.2.2. Efficiency in Real-Time Control

These experimental results further signify that the PNLMPC is effective for real-time applications, supported by the shortest CPU simulation time with respect to both standard and adaptive MPC methods. This proves that this framework is capable of fast, efficient, and reliable control, hence fit for practical MG operations.

5.2.3. Technical and Economic Performance

The contribution of this thesis represents a significant enhancement of traditional control methods represented by standard MPC and adaptive MPC. At islanded mode, this framework demonstrates an 85.87% reduction in total voltage deviation compared to standard MPC and an 87.62% increase compared to adaptive MPC. Economically, this approach reduces the operational cost by 39.29% compared with standard MPC and by 28.12% compared with adaptive MPC, underscoring the potential of the framework in terms of cost-efficient energy management. In grid-connected MG applications, the proposed framework presents very important voltage deviations of 37.5% compared to the adaptive MPC strategy and 73.68% compared to standard MPC strategies. The proposed framework also performs better from an economic viewpoint, reducing costs by about 24.19% compared to standard MPC and about 35.83% compared to adaptive MPC. Results verify the flexibility and strength of the proposed framework for real-time MG control both from a technical and economic point of view and, consequently, represent a promising solution for practical applications.

5.3. LIMITATIONS

The main limitations of this study are listed below:

5.3.1. Economic Feasibility

While the research aims to optimize economic aspects, the actual implementation costs of the proposed hierarchical control systems may vary, and the study will not conduct a detailed economic analysis of the deployment.

5.3.2. Environmental Factors

The study will primarily focus on power control strategies and may not extensively address the environmental impacts of RES or variations in energy demand due to external factors.

5.3.3. Complexity of Hybrid Systems

The control of hybrid AC/DC MGs introduces complexity; while the study will address this, some intricacies related to system design and operation may not be fully explored.

5.3.4. Simulation Limitations

Results derived from MATLAB simulations may not fully capture real-world conditions, including unforeseen operational challenges that could arise in actual MG environments.

5.4. RECOMMENDATIONS FOR FUTURE STUDIES

These encouraging results of this thesis will be used as a basis for future work in the following areas to enhance the PNLMPC framework further:

5.4.1. Scalability and computational efficiency

This work showed that PNLMPC can handle both islanded MG and grid-connected situations. In any case, scalability and computational efficiency have to be refined for larger and more complex MG systems in future studies.

5.4.2. Economic Factors and Policy Impacts

Future research should therefore be directed at economic factors, market conditions, and policy changes that may impact the performance of the PNLMPC framework. Simulations of different regulatory and market scenarios may be studied for such factors that affect overall efficiency and cost-effectiveness so that the framework will be adaptive to changing energy markets.

5.4.3. Resilience and Sustainability

Further studies will be needed to understand how this PNLMPC framework can be used to expand the resiliency and sustainability of MGs in view of higher renewable energy penetrations and emerging energy challenges.

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RESUME

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