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Review

A Systematic Review and Meta-Analysis of Model Predictive Control in Microgrids: Moving Beyond Traditional Methods

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Abstract

Microgrids are gaining considerable attention as a promising solution for integrating distributed energy resources and enhancing grid resilience. Model predictive control (MPC) has emerged as a powerful control strategy for microgrids due to its ability to handle complex dynamics and optimization problems. This study aims to conduct a comprehensive assessment of MPC applications and evaluate their overall effectiveness across various microgrid functionalities. Previous studies have not collectively examined MPC and have not explored its advantages and disadvantages in the microgrid. This study systematically categorizes and addresses this gap in the existing literature. An extensive list of suitable research papers was compiled from the Web of Science and analyzed, considering the method of the studies, main focus and objectives, publication year, and findings. Moreover, this research incorporates co-occurrence keyword analysis, covering MPC applications, systematic reviews, microgrids, and review articles. The visualization and analysis of the data obtained from the Web of Science database were conducted using VOS viewer. This discussion includes approaches that help electrical engineers evaluate the benefits and disadvantages of MPC within the microgrid setup. This knowledge enables electrical practitioners to select the appropriate methods for providing a resilient and reliable ecosystem.

Keywords: model predictive control; microgrid; distributed energy resources; electrical engineering

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1. Introduction

The rising interest in microgrids (MGs) offers valuable opportunities for the future of power systems. These small-scale grids present solutions to improve grid reliability, decrease environmental impact, and promote the use of environmentally friendly energy sources [1]. As one of the foundational elements of next-generation smart grid infrastructure, MGs play a critical role in reducing power losses, improving power quality, reducing pollutant emissions, and enhancing grid resilience [1,2]. While there is no general definition,

MGs are commonly recognized as single, synchronized, and controllable power units that combine distributed energy resources, flexible loads, and energy storage devices [1,3,4]. Additionally, MGs engage with medium-voltage and low-voltage distribution networks within power systems and can operate in either grid-connected or island modes [4,5]. In contrast to traditional centralized electricity grids, which have limited flexibility in generation and load control, smart MGs operate as semi-independent units capable of efficiently managing energy generation and load operations [5]. These systems provide bidirectional power flows and enhanced operational autonomy, which are not commonly found in conventional electricity networks [6,7]. MGs have emerged as a valuable solution in response to the increasing energy demand, environmental concerns, and the need for distributed and resilient power systems [8,9]. In addition, their energy-related benefits, MGs improve security and reliability by separating crucial infrastructure from the primary grid, making them less vulnerable to cyber-attacks [10]. Because of the dynamic and uncertain nature of the MG environment, intelligent control strategies have become the most effective method for ensuring optimal performance [1].

Among them, model predictive control (MPC) has gained wide acceptance as an effective and robust control method for MGs. MPC has emerged as a sophisticated control strategy for MGs since it can manage complex system dynamics, constraints, and multi-objective [11,12]. The potential of MPC to enhance system performance is based on its ability to combine the strengths of predictive model control, like simplicity of implementation and fast dynamic response, with acceptable power quality at low sampling frequencies. This makes it a suitable candidate for MG control, enabling efficient and reliable operation [13,14]. MPC is a control method that employs an analytical model of the system to optimize its performance [12,15–17]. It forecasts the future behavior of the system and determines the best control inputs to achieve desired targets [17,18]. This adaptability and predictive ability make MPC suitable for managing distributed energy resources and handling nonlinearities, competing objectives, and operational constraints in MG [17,19].

Despite numerous studies demonstrating the effectiveness of MPC in microgrids, the literature remains fragmented. Few reviews systematically compare algorithmic variants, assess multi-objective optimization strategies, or evaluate the integration of MPC within hybrid and hierarchical control frameworks. This review paper discusses the peer-reviewed literature published from 2016 to 2025, focusing on MPC-based control strategies for operating MGs with regard to optimization, implementation challenges, and future designs. The main contributions of this paper are as follows:

- Provides a comprehensive classification of MPC techniques applied in MGs based on objectives, algorithms, and application domains;
- Analyses the use of multi-objective optimization and highlights its role in enhancing operational trade-offs in MGs;
- Explores the integration of MPC with hybrid and hierarchical control strategies for complex, real-world implementations;
- Offers a bibliometric meta-analysis to uncover research trends and publication patterns over the past decade.

Figure 1 illustrates the methodology applied in this review paper to thoroughly analyze the role and applications of MPC in microgrids. A better understanding of this area of study is obtained by the combination of the systematic review method and bibliometric analysis. While systematic review guarantees the identification, screening, and synthesis of related studies, bibliometric analysis presents quantitative information through publication trends and citation networks in MPC in MGs. These outlined approaches guide electrical engineers and researchers to better understand the weaknesses and strengths of MPC applications within MGs. The literature review shows that much of the research emphasizes

multi-objective optimization (MOO) and hybrid control strategies. Such strategies are important for applying demand-response programs, which modify energy consumption based on grid conditions or market signals. This capability is particularly crucial during MG transitions from grid-connected to islanding modes for ensuring a smooth restoration process upon reconnection to the main grid. This review aims to assist practitioners of electrical engineers in selecting the most suitable MPC approaches to gain robust and resilient MGs.

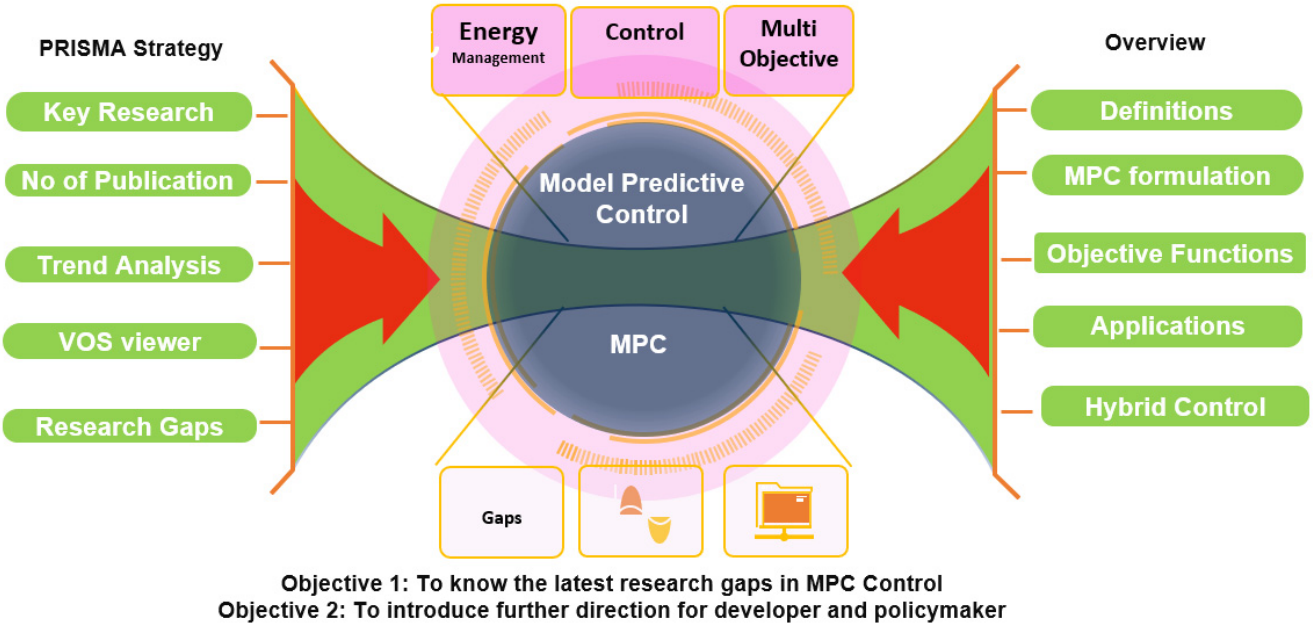


Figure 1. Strategy for analyzing literature reviews.

The meta-analysis section of this study provides significant insights into the quantitative nature of the research literature on MPC in MGs. For the validation of this analysis, the Web of Science (WOS) database was used for keyword analysis. Figure 2 presents the network of interconnected keywords based on MPC applications in MGs from 2021 to 2025. This network was generated by using the VOS viewer (1.6.19) software. The size and labeling of each node correspond to the prominence of the respective keyword, while connecting lines signify associations between them. Furthermore, distinct colors signify separate clusters based on their specific areas of expertise [20]. As shown in this figure, emerging themes such as "AI-based predictive control", "hybrid microgrid resilience", and "real-time energy management" reflect an increasing research focus. These thematic clusters indicate an increased interest in intelligent and adaptive MPC strategies designed to address the uncertainties and complexities of modern MGs.

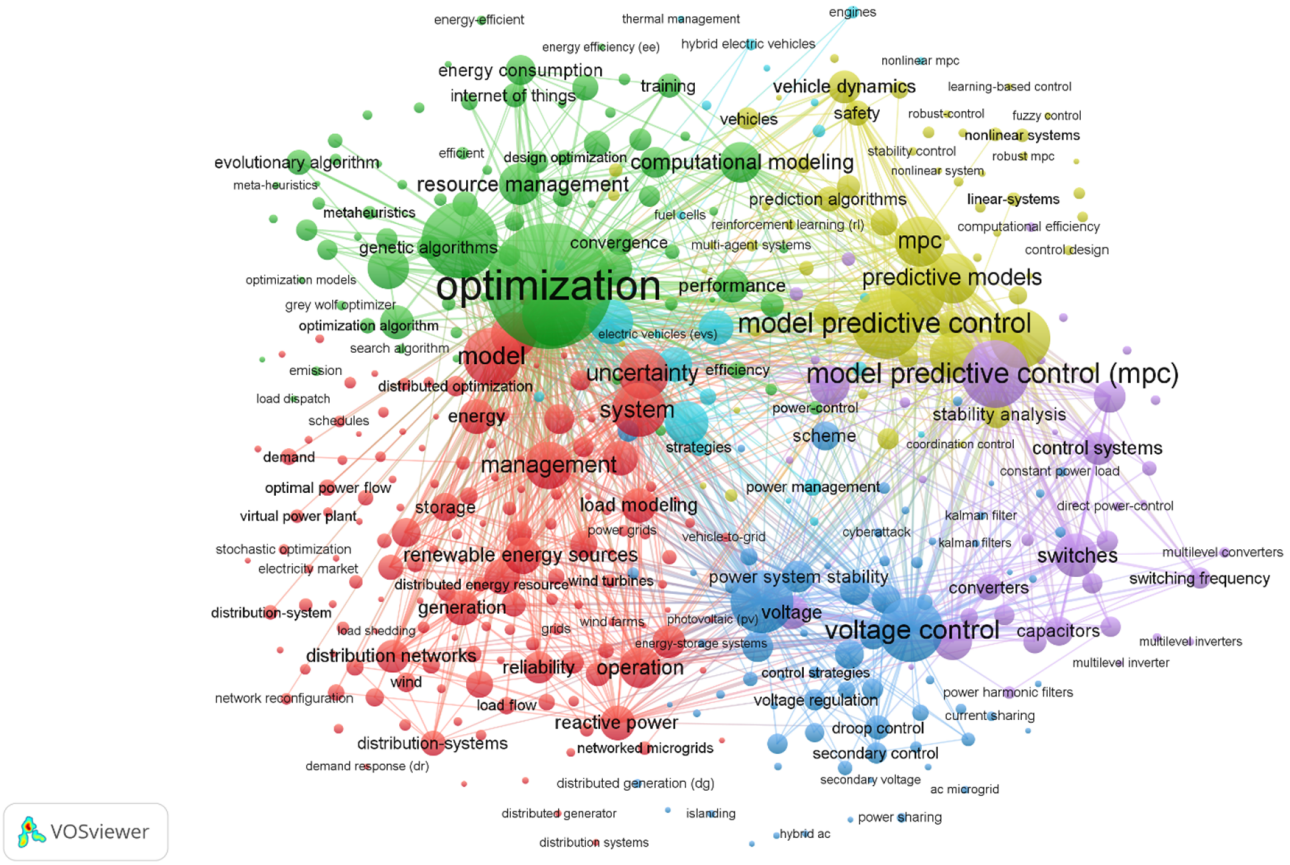


Figure 2. Visualization of MPC implementation in MGs based on total publications, supported by data retrieved from the WOS database.

2. Background and Review Methodology

2.1. MPC Fundamentals and Microgrid Applications

Microgrids, encompassing distributed energy resources, energy storage units, and smart control infrastructure, offer a reliable and resilient power-supply solution to end-users. This decentralized approach effectively addresses the limitations of centralized power systems [21,22]. MGs come in various types, each designed to meet specific needs and operate under different conditions. MGs can be classified both by configuration and operational mode. In terms of configuration, these are categorized into three varieties: AC, DC, and hybrid AC/DC MGs [23,24]. In terms of operation, MGs are classified as grid-connected, islanded, or in transition between these two states [25,26]. In grid-connected mode, the primary network provides voltage and frequency support, with distributed generators (DGs) focusing solely on power generation. However, controlling frequency is a significant challenge in islanded microgrids, often composed of non-inertial sources linked through power electronic converters [27,28]. Islanded MGs are commonly implemented in remote locations, where establishing a connection to the national power grid is not practical. In this mode, DGs regulate voltage and frequency. Yet, due to inherent uncertainty in power production from dispersed sources, energy storage devices like batteries and supercapacitors become essential to compensate for production and demand fluctuations [29]. Efficient energy management is crucial in such a context [30]. A proposed solution for frequency control in MGs involves the implementation of virtual inertia using the characteristics of MPC [28,31].

Given that several renewable energy sources produce direct current, and various electronic and control equipment require DC voltage, researchers advocate for DC MGs to enhance system efficiency [32–34]. The advantages of DC microgrids, such as the absence of

resource synchronization requirements, lower losses compared to AC systems, lack of reactive power and skin effect, increased transmission line capacity, and simpler control, make them an attractive option for research. Although the skin effect is minimal in low-frequency AC systems (such as 50 Hz), its complete absence in DC systems still contributes to greater efficiency, especially in compact or high-current applications. Despite the benefits of DC microgrids, it is not economically feasible to overhaul existing networks due to established distribution network structures and the prevalence of electrical appliances designed for AC input. Consequently, researchers prioritize optimal control of AC microgrids, focusing on areas like energy management [35–37], power quality [38,39], and interfacing converter structures [40,41].

In AC microgrids, DGs like diesel generators are directly connected to the grid, while others, such as photovoltaic and fuel cells, are linked through a power electronic interface converter. DGs with interface converters lack inertia, affecting MG stability. However, virtual inertia, implemented through MPC, can mitigate this drawback [42]. These converters, when used at their full capacity, can enhance power quality indicators like harmonic reduction and reactive power injection [38,42]. Hybrid AC-DC MGs efficiently utilize DGs, AC, and DC loads, comprising two sub-grids (AC and DC) connected by an interlinking converter [43,44]. These MGs combine the advantages of AC and DC types, reducing the number of converter layers and associated losses. However, their control and operation are more complex than individual AC and DC microgrids, especially when incorporating energy storage sources [45]. Despite the complexity, the advantages position hybrid MGs as potential future MG solutions [46,47].

Modern MGs operate in increasingly dynamic environments shaped by fluctuating loads, intermittent renewable energy sources, converter-based interfaces, and operational transitions between grid-connected and islanded modes. These complexities make it challenging to maintain stability, ensure optimal resource utilization, and satisfy both technical and economic objectives. MPC addresses these challenges through a prediction-optimization framework that continuously adjusts control actions in real time. At each time step, MPC uses a dynamic system model to forecast future states over a defined horizon, solves a constrained optimization problem to minimize a specified objective function, and applies only the first control input in the optimized sequence. This process, repeated in a receding horizon fashion, enables MPC to adapt to disturbances and evolving grid conditions in a closed-loop manner [17,18]. In grid-connected microgrids, MPC facilitates coordinated energy dispatch between distributed energy resources, storage systems, and the main grid. It supports peak-shaving, demand-response, and cost-minimization strategies by forecasting consumption and generation patterns [39,48]. In islanded operation, where the system must operate autonomously, MPC is especially valuable for voltage and frequency regulation in the absence of grid support. It enables the implementation of virtual inertia through advanced converter control, enhancing dynamic stability in low-inertia environments [19,49]. Moreover, MPC manages transitions between operational modes, such as reconnection after islanding, by enforcing synchronization constraints and load balancing [26].

Hybrid AC/DC microgrids present additional challenges due to the presence of asynchronous subsystems and the need to coordinate power flow through interlinking converters [40,46]. MPC optimizes control actions across both domains by dynamically adjusting converter setpoints, ensuring system-wide stability while minimizing conversion losses. Furthermore, the controller can accommodate operational constraints such as state-of-charge (SoC) limits, ramp rates, thermal limits, and grid-code compliance, all of which are explicitly formulated in the optimization problem [19,49]. In practical implementations, MPC has also been adapted for distributed frameworks (DMPC), where each microgrid

or subsystem executes its local optimization while exchanging limited information with other agents [50,51]. This structure supports scalability and modularity in multi-microgrid networks. Whether centralized or decentralized, MPC enables complex objectives, such as reliability, efficiency, emissions reduction, and resilience, to be addressed simultaneously, making it an indispensable tool in advanced microgrid control [52].

2.2. Research Gap and Review Positioning

Despite the growing body of literature on MPC in MGs, existing reviews often address narrow technical scopes and lack a comprehensive synthesis of algorithmic, architectural, and application-level perspectives. Many studies focus exclusively on specific control types, such as economic MPC or converter-level control, without discussing broader system integration, multi-objective trade-offs, or scalability challenges. For instance, economic MPC is extensively presented in [53,54], whereas hybrid MPC controllers that combine rule-based and predictive strategies are investigated in [55,56].

Others examine algorithmic developments in isolation, with limited attention to practical deployment constraints or compatibility with hierarchical control structures. Moreover, there is a notable lack of bibliometric insight into publication trends, thematic focus areas, and collaboration networks that shape the research landscape.

A review of the recent literature reveals that topics such as multi-objective optimization, DMPC, and hybrid control strategies are either partially explored or treated in isolation. For example, although multi-objective formulations are essential for balancing competing goals like cost, power quality, and reliability, only a few works examine their implementation in actual microgrid control scenarios. Approximately 18% of the selected studies involve real-world MG implementations or hardware-in-the-loop validations, while the remaining are simulation-based. Similarly, while hybrid MPC architectures—combining predictive control with rule-based, PID, or fuzzy logic controllers—are gaining traction, existing reviews rarely analyze their comparative performance or integration complexity. Furthermore, the role of MPC in managing complex microgrid dynamics, particularly in hybrid AC/DC configurations or in systems requiring real-time reconfiguration, is insufficiently covered in most prior surveys.

This review aims to bridge these gaps by presenting a structured and extensive analysis of MPC strategies across various microgrid types and control objectives. In addition to reviewing technical implementation aspects, this study conducts a bibliometric evaluation using data extracted from the WOS database, with keyword co-occurrence mapping performed via VOSviewer. This review comprehensively evaluates MPC algorithm classes, objective function designs, constraint-handling approaches, and integration strategies with higher-level control systems. It also contrasts existing studies in terms of their scope, application domains, and methodological depth, as summarized in Table 1. By synthesizing both theoretical and data-driven insights, this work provides a clear understanding of where the field stands, what challenges remain, and how future research can evolve to meet the control demands of next-generation microgrids. Table 1 outlines various review articles conducted by researchers on the predictive control model of microgrids from 2019 onward. Unlike these reviews, which concentrate on two or more techniques, our review paper takes a thorough approach by extensively exploring each technique within the predictive control modeling of MGs. This study employed a keyword analysis, simultaneously exploring terms like MPC, MGs, and systematic review, and utilizing data from the WOS database.

Table 1. Summary of review articles and addressed gaps.

Ref.	Scope of Review	MPC in MGs	MOO in MPC	Hybrid Control	Hierarchical Strategy in MGs	Real world Insights	Gap Address in This Study
[53]	Thematic; general	✓	✓	×	✓	×	Lacks hybrid/ control diversity
[57]	Focuses on MG control	✓	✓	×	✓	×	Limited structure and hierarchy
[58]	Structured but narrow	✓	✓	×	✓	×	Lacks hybrid control and real-world focus
[59,60]	Algorithm centric	✓	×	×	×	×	Lacks application perspective
[61–63]	Practical but partial focus	✓	×	×	×	×	No hybrid or hierarchical view
[64]	Predictive power management in hybrid RES	✓	×	✓	×	×	Lacks control taxonomy, real-world cases, and MOO
[65]	Evaluation of MPC-based MPPT for PV systems	✓	×	×	×	✓	Lacks MOO and hybrid/ hierarchical control
This study	Comprehensive (taxonomy + application)	✓	✓	✓	✓	✓	Unified taxonomy, hybrid control, MOO, and real-world integration

2.3. Review Methodology and Bibliometric Analysis Approach

To ensure a structured, comprehensive, and objective evaluation of MPC applications in microgrids, this study adopts a hybrid methodology that integrates both systematic review techniques and bibliometric analysis. This dual approach enables the identification of the relevant literature, assessment of research patterns, and extraction of thematic insights critical to understanding the evolution and scope of MPC-based microgrid control strategies. Our review process followed standard guidelines for systematic literature reviews (SLRs), including planning, screening, eligibility assessment, and synthesis. The initial step involved formulating the research questions and defining the inclusion and exclusion criteria. The primary questions guiding this review were as follows:

- What are the dominant MPC strategies used in microgrid control?
- How do these strategies vary by application (energy management and frequency control)?
- What control objectives and optimization techniques are employed?
- What research gaps exist in terms of hybrid, hierarchical, and multi-objective implementations?

A timeline examination of publication trends reveals a sharp surge in MPC-based MG research before and after 2020. The surge reflects an increased focus on energy resilience, AI deployment, and distributed control in post-pandemic smart-grid planning.

Data Collection and Source Selection:

Relevant publications were sourced from one major academic database, WOS, covering the period from 2016 to 2025. This database was chosen due to its extensive coverage of peer-reviewed engineering, control systems, and energy-related research. The initial search string included combinations of the following keywords:

To search for relevant studies, a group of keywords was used in both the *Title* and *Topic* fields. Using the *AND* operator, "*Power System*" and "*Model Predictive Control (MPC)*" were the keywords used in the *Title* field, and "*Control Strategies*" was used in the *Topic* field to spotlight the areas of concern.

To cover more areas and similar research, other keywords were employed together with the *OR* operator. These include "*Distributed Energy Resources*", "*Optimization*", "*MPC*", "*Multi-Objective Optimization*", and "*Model Predictive Control (MPC)*" in *Topic*, and "*Microgrids*", "*DC Microgrids*", "*AC Microgrids*", and "*Hybrid Microgrids*" in *Title*. This ensured wide coverage of the scientific literature concerning model predictive control in power systems and microgrids.

The inclusion and exclusion criteria utilized to choose the publications are presented below in Table 2, covering aspects such as time range, language, document type, subject area, search logic, and source database.

Table 2. Criteria used for filtering relevant publications.

Criteria	Inclusion	Exclusion
Time range	2021–2025	Publications before 2021 or after 2025
Language	English only	Non-English publications
Document type	Research articles, review papers	Conference abstracts, editorials, etc.
Subject area	Electrical engineering	Other fields of engineering or unrelated fields
Search logic	Applied AND, OR for specific filtering	-
Source database	WOS	Other databases (e.g., IEEE Xplore)
Publishers	All publishers indexed in WOS	-

3. Overview of MPC Approaches in Microgrid

MPC uses the explicit model of the system to attain control objectives [66,67]. It continuously adjusts control inputs based on real-time feedback and future predictions, making it a powerful closed-loop strategy [18,67–69]. There are numerous algorithms that can be used by application developers for MPC; however, each has its pros and cons [70,71]. The selection of an algorithm is contingent upon several factors, encompassing the particular configuration of the MG [72,73], control objectives [74,75], computational constraints [76,77], and available hardware resources [78].

3.1. System Dynamics in MPC

In the domain of control systems such as MPC, algorithms operate within a realm of continuous system dynamics [79]. This means that the system under control obeys continuous time derivatives, which implies that its behavior evolves in a uniform manner over time, without any sudden breaks or sudden stops [79,80]. The distinction between discrete and continuous formulations in control algorithms hinges on the representation of time and the modeling of system dynamics. Therefore, algorithm selection needs to consider not only computational factors but also the dynamics of the controlled system. While many algorithms for MPC utilize continuous system dynamics [81–86], some incorporate discrete system dynamics [87]. The differentiation between discrete and continuous formulations relies on how time is represented and how system dynamics are modeled, both of which are introduced here.

- In continuous system dynamics, time is conceptualized as a continuous variable, facilitating seamless and uninterrupted changes in the system's state [61,88]. Characterized by continuous-time differential equations, these equations elucidate the rate of change in the system's state variables over time [89,90]:

$$\frac{dX_{(t)}}{d(t)} = f\left(X_{(t)}, u_{(t)}\right) \quad (1)$$

where $X_{(t)}$ represents the state of the system at time, t; $u_{(t)}$ represents the control input at time, t; and f characterizes the continuous dynamics function, delineating the evolution of system over time.

- In discrete system dynamics, time is segmented into discrete intervals, with system state alterations occurring solely at these specified time steps [91,92]. Equation (2), captured by the systems, delineates how the state proceeds from one time step to the other with different equations [93].

$$X_{(t+1)} = g\left(X_{(t)}, u_{(t)}\right) \quad (2)$$

where $X_{(t)}$ denotes the system's state at the current time step (t), $X_{(t+1)}$ represents the system's state at the subsequent time step $(t+1)$, $u_{(t)}$ signifies the control input applied at the current time step (t), and g defines the system dynamics as a function of the preceding state and control input. System dynamics can be applied to discrete and continuous MPC methodologies based on the characteristics of the system [94,95]. The pivotal distinction lies in how time is conceptualized and how system dynamics are represented, as delineated by the respective formulas [95]. Furthermore, the objective function presents another crucial factor to consider when selecting MPC algorithms. Various types of objective functions for MPC algorithms are chosen based on the specific control objectives required. Table 3 shows the classification of objective functions in MPC methods.

Table 3. Overview of MPC objective function types with descriptions and formulations.

Category	Description	Key Formula	Ref.
Single objective	A single goal (such as the reduction of errors or energy consumption) is optimized. This optimization involves only a single variable.	$J(x,u) = (x(t) - x_{desired}(t))^2$	[96,97]
Multi-objective	Several objectives are considered together, and these objectives can be prioritized by using weights.	$J(x,u) = \omega_1 \cdot (x(t)x_{desired}(t))^2 + \omega_2 \cdot u(t)^2$ (With weights ω_1 and ω_2)	[98,99]
Adaptive objective	The function dynamically changes according to system conditions. It adjusts based on past data and current inputs.	$J(x,u,t) =$ $func$(previous data, current state, control input, time)	[100–102]
Learned objective	This function uses neural networks (NNs) to automatically simulate the goal. It is useful for modeling complex, nonlinear relationships.	$J(x,u) = FNN(x,u)$ (NN trained to model the objective)	[103–106]
Distributed objective	In multi-agent systems, each agent accomplishes its specific goal, ultimately resulting in a global goal.	$(x,u) = \sum_{i}^{N} J_i(x_i, u_i)$ (N is the number of agents)	[107,108]

Table 3. *Cont.*

Category	Description	Key Formula	Ref.
Robust objective	This function is designed to manage uncertainties or disturbances in the system. It optimizes under the largest possible disturbances.	$J(x,u) = min(max(J_{robust}(x,u,d)))$ (d is the disturbance parameter)	[109–112]
Economic objective	This function maximizes economic aspects such as cost or profit, emphasizing the economic contribution of system decisions.	$J(x,u) = (R_{\text{revenue}}(x) - Cost(u))$ (R_{revenue} is the revenue and $Cost(u)$ is cost)	[48,113]
Mixed-integer objective	This function includes continuous and discrete (integer or binary) variables. It introduces additional complexity.	$J(x) = f(x_c, x_d)$ (x_c are continuous variables and x_d are discrete variables)	[114,115]
Quadratic objective	This function is expressed as a quadratic form of state and control variables, and convex optimization is used for optimization.	$J(x,u) = \frac{1}{2}x(t)'Qx(t) + \frac{1}{2}u(t)'Ru(t) + \cdots$	[116–118]

3.2. Types of Objective Functions in MPC

Having established the distinction between continuous and discrete system dynamics, the next logical step in designing MPC strategies for microgrids is the careful selection of objective functions. These functions define what the control system aims to optimize and play a critical role in shaping system behavior [70,71]. Once appropriate objective functions are defined, they must be addressed through suitable optimization techniques. A variety of MPC algorithms have been developed to tackle different control challenges in microgrids, each with distinct advantages, computational requirements, and application scopes [119,120]. In MPC, the objective function is a central element that dictates how control actions are optimized over the prediction horizon. In the context of microgrids, where multiple DERs, energy storage units, and load profiles interact dynamically, the choice of objective function plays a critical role in achieving control goals [19]. Objective functions in MPC can vary significantly depending on whether the priority is economic performance, technical stability, environmental sustainability, or robustness against uncertainty [111,112]. These functions are often formulated as mathematical expressions that quantify control performance, typically by minimizing cost, tracking errors, or deviations from operational constraints. Since microgrid environments are heterogeneous and prone to disturbances, tailoring the objective function to reflect real-world control demands is essential for practical effectiveness [121]. To accommodate diverse operational needs, objective functions in MPC can be classified into several categories. Single-objective functions aim to minimize or maximize a single performance criterion, such as energy cost or voltage deviation [96,97]. In contrast, multi-objective functions balance competing goals—like minimizing emissions while maximizing renewable utilization—often using weighted sums or Pareto optimization [114,115]. Economic objectives focus on minimizing operating costs or maximizing profits, particularly relevant in market-integrated MGs [122,123]. Adaptive and learned objectives evolve in real time or are shaped by machine learning models to cope with dynamic conditions or unknown system behaviors [124–126]. Other categories include robust objectives, which account for uncertainty in inputs or models [111,112]; dis-

tributed objectives for multi-agent systems [127]; and mixed-integer [114,115] or quadratic objectives [117], which represent discrete decisions or linear systems, respectively. Table 4 provides a detailed breakdown of these objective function types, their definitions, mathematical formulations, and representative studies in the literature. Figure 3 illustrates the overview of these objective functions in MPC.

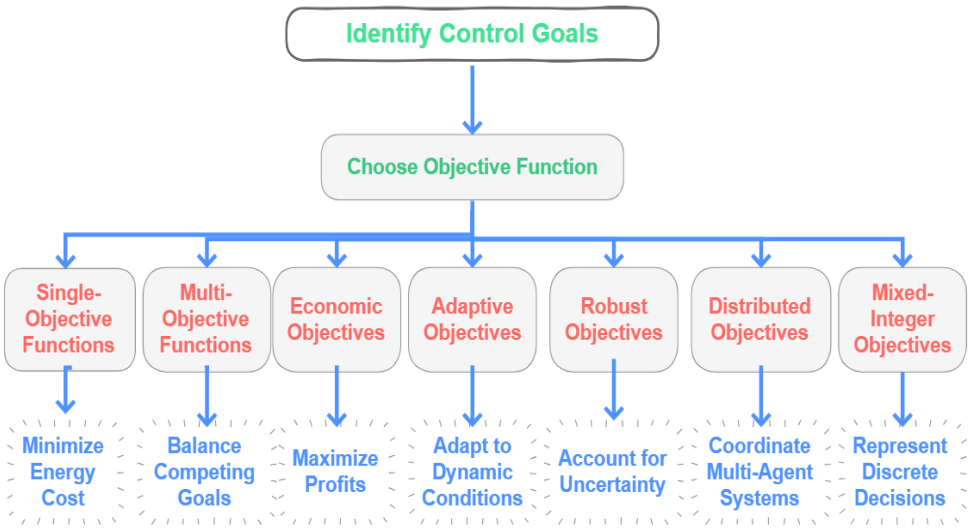


Figure 3. Classification of objective functions in MPC.

3.3. MPC Algorithm Types (Formulation-Based)

Once an appropriate objective function is developed, the second important step in MPC design is the selection of an optimization structure or algorithm, which is closely related to the complexity of the system, the variable types, and the computational requirement. These formulation-based classifications define how the cost function is structured, how constraints are handled, and what assumptions are made about the system model. Each type of MPC algorithm offers different trade-offs between computational complexity, system performance, and robustness, making the selection process crucial in MG control design. This section presents key algorithm classes used in MGs, with a focus on their formulation logic, application suitability, and practical limitations. To provide a systematic concept of diversity within MPC algorithms, they can be broadly classified into two types based on their primary focus: (1) algorithms toward control objectives, and (2) optimization problem-solving approach-driven algorithms. Both categories offer unique benefits in MPC systems, especially for flexibility, robustness, computational complexity, and practicability. Figure 4 provides a visual representation of this classification, and each of these categories is explained in detail below.

(1) Control-Oriented Classification of MPCs

These algorithms are primarily distinguished based on their control objectives, like robustness, adaptability, economic performance, and learning-based behavior. Each of the following methods modifies the MPC cost function or prediction model to fit specific operating goals:

- Linear Quadratic Regulator (LQR): LQR is a preferred choice in MPC applications due to its simplicity and computational efficiency [128,129]. However, its simplicity comes at a cost, as it is primarily suited for linear systems with quadratic cost functions. To address these limitations, researchers have proposed various approaches, including a novel LQR controller that tackles V-f control in isolated PV–battery MGs [130]. This controller eliminates state estimators, relies on local data, and handles diverse

uncertainties, achieving robust performance verified by extensive HIL tests. Building on this success, Reference [131] introduces an even more robust combo of resonant and lead–lag controllers. This approach tackles voltage tracking and stability in isolated MGs, outperforming LQR, MPC, and NI controllers by handling diverse uncertainties and offering excellent tracking, enhanced stability, and flexibility across single- and three-phase systems.

- Economic Model Predictive Control (EMPC): EMPC integrates economic considerations into the MPC framework, optimizing control decisions to either maximize economic profit or minimize operational costs [19,53,54].
- Robust Model Predictive Control (RMPC): RMPC tackles uncertainties in system dynamics or model parameters by integrating robustness constraints into the optimization problem [132]. This ensures stable performance, particularly in the face of uncertain conditions [133].
- Neural network-based MPC (NNMPC): NNMPC employs neural networks to learn system dynamics and control policies. It is particularly useful for complex nonlinear systems where traditional modeling approaches are challenging [134,135].
- Adaptive Model Predictive Control (AMPC): AMPC dynamically updates the system model and control parameters based on real-time feedback, adapting to changing system conditions and uncertainties [136,137].

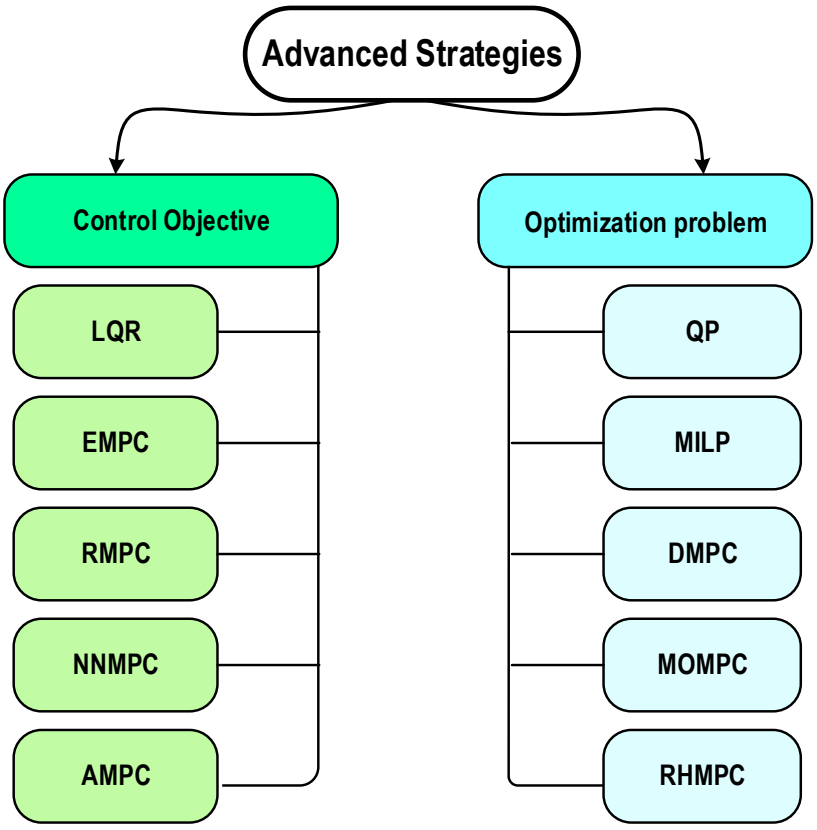


Figure 4. Visualization of advanced MPC optimization strategies.

(2) Optimization Problem-Based MPC

This category emphasizes the formulation and solution of optimization problems in the context of MPC. Employing different solver types and formulations, these methods expand the capacity of MPC to handle high-dimensional, complex, or mixed-variable systems.

- Quadratic Programming (QP): QP emerges as a more versatile optimization algorithm capable of managing nonlinear systems and non-quadratic cost functions [138,139]. Although more computationally intensive than LQR, QP offers increased flexibility.
- Mixed-Integer Linear Programming (MILP): MILP finds application in MPC scenarios with discrete decision variables, addressing tasks like switching between energy sources or adjusting power setpoints [140,141]. While computationally more demanding than QP, MILP excels in optimizing intricate discrete control strategies [142,143].
- Distributed Model Predictive Control (DMPC): DMPC finds application in large-scale MGs characterized by decentralized control architectures [50,51]. It divides the optimization problem into smaller subproblems, facilitating distributed computation and minimizing communication overhead [144,145].
- Multi-Objective Model Predictive Control (MOMPC): MOMPC optimizes multiple conflicting objectives simultaneously, finding trade-offs between competing goals such as economic efficiency, environmental impact, or system stability [146,147].
- Receding-Horizon MPC (RHMPC): RHMPC is an iterative implementation strategy for MPC [148,149]. It repeatedly solves the optimization problem over a finite horizon, rolling the horizon forward with each iteration to adapt to changing conditions [149,150].

Figure 5 graphically illustrates the interrelation between the major control objectives in MG MPC—economic, technical, environmental, and adaptive—and their corresponding MPC types. This figure provides a simple yet comprehensive overview of how MPC algorithms are selected based on control objectives, complementing the more detailed classification in Figure 3.

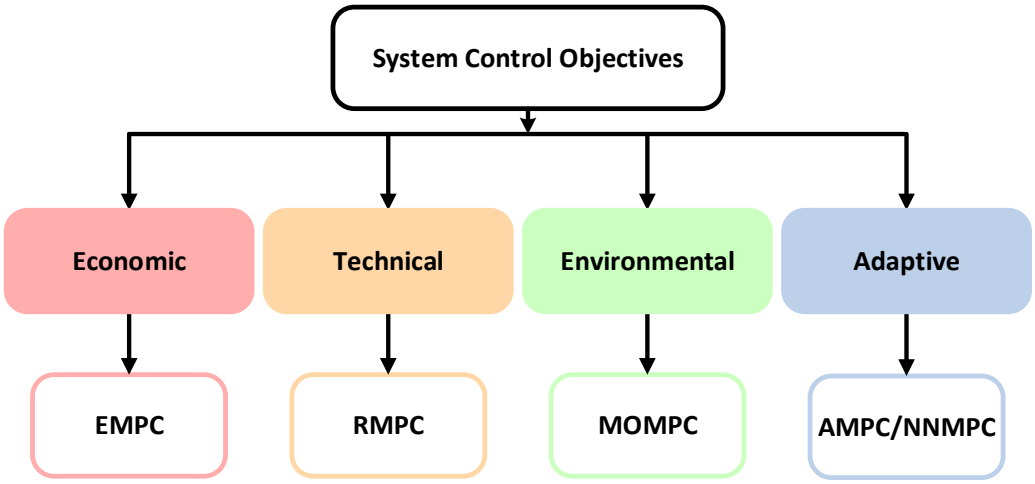


Figure 5. Alignment of MG control objectives with MPC strategies.

Table 4 provides a comparative overview of these MPC algorithm types, highlighting their system dynamics assumptions, objective function types, optimization formulations, computational complexity, and MG application domains. In order to provide a more structured overview of the primary MPC approaches employed in MG control, Table 5 presents a comparative summary of the main techniques, their key application areas, common performance metrics, and existing research gaps. This classification assists in identifying suitable algorithms based on the control goals, resource availability, and the specific operating conditions of the MG.

Table 4. Comparison of MPC variants.

Algorithm	System Dynamics	Objective Function	Optimization Problem	Computational Complexity	Applications
RHMPC [81,82]	Continuous	Single	QP	Moderate	General control
MOMPC [151]	Continuous	Multiple	Multi-objective QP	High	Multi-objective control
AMPC [83]	Continuous	Adaptive	Adaptive QP	High	Adaptive control
NNMPC [84]	Continuous	Learned	Neural network	High	Nonlinear control
DMPC [52]	Distributed	Distributed	Distributed QP	High	Large-scale systems
RMPC [85,86]	Continuous	Robust	Robust QP	High	Robust control
EMPC [152]	Continuous	Economic	MILP	High	Economic optimization
MILP [87]	Discrete/ Continuous	Mixed-integer	MILP	High	Discrete/continuous systems
QP [153–156]	Continuous	Quadratic	QP	Moderate	General control
LQR [157]	Continuous	Quadratic	Riccati equation	Moderate	Linear systems

Table 5. Summary of MPC techniques, application areas, performance metrics, and research gaps.

MPC Technique	Application Area	Performance Indicator	Identified Research Gaps
EMPC [95,158]	Cost optimization in MGs	Operational cost reduction	Limited real-time implementation
DMPC [159–161]	Multi-agent distributed MGs	Scalability, flexibility	Communication overhead, convergence delays
MOMPC [146,162]	Multi-objective energy management	Pareto efficiency	Computational complexity
RHMPC [160,163,164]	Islanding transition and fault recovery	Fast frequency/voltage control	Requirement of high-frequency data, instability risks
AMPC [83,165]	Dynamic and uncertain loads	Robust response to system changes	Adaptive model-tuning complexity
NNMPC [166,167]	Nonlinear system control	Tracking accuracy, generalization	Training data dependency, real time interface challenges
RMPC [85,86,168]	Uncertainty resilient control	Robustness against disturbances	Conservative performance, complex constraint handling
MILP [169,170]	Scheduling and resource optimization	Global optimality	Scalability and combinatorial explosion
QP [171,172]	Fast linear MPC formulations	Computation time, feasibility	Inflexibility in nonlinear/complex system
LQR [173,174]	Linear quadric control in stable MGs	Control effort, response speed	Limited adaptability, assumption of linear dynamics

3.4. MPC Strategies (Deployment/Architecture-Based)

Beyond the formulation of objective functions and optimization problems, MPC strategies can also be classified based on how they are deployed architecturally within a system. These deployment-based strategies reflect how the control logic is distributed across subsystems, how decisions are coordinated, and how computational tasks are handled in

real-time operations. The distinction between centralized and distributed architectures is central to this classification, especially in MGs, where scalability, resilience, and communication constraints significantly influence the choice of strategy [21,22]. In centralized MPC, a single controller gathers system-wide data, solves the optimization problem globally, and dispatches control actions to all units [50,51]. While this allows for optimal global coordination, it is often impractical for large-scale or modular MGs due to communication overhead, latency, and computational burden. In contrast, DMPC decomposes the global problem into smaller sub-problems assigned to local controllers. Each agent (e.g., a DER or microgrid cell) solves its local optimization while sharing limited information with neighbors or a coordinating entity. DMPC enhances scalability, robustness, and privacy, making it well-suited for multi-microgrid systems or islanded operations [144,145]. RHMPC is a temporal deployment strategy where optimization is continuously performed over a shifting time horizon. At each step, only the first control input of the optimized sequence is implemented, and the horizon moves forward in time. This iterative approach improves real-time adaptability and robustness to disturbances or forecast inaccuracies [149,150]. Hierarchical MPC introduces layered control levels—primary, secondary, and tertiary—each with distinct timescales and functions. Higher layers handle long-term economic dispatch or energy scheduling, while lower layers manage fast dynamics, like voltage and frequency regulation. This architecture aligns well with the layered structure of power systems and supports modular integration of diverse assets [61,175,176]. Finally, hybrid MPC strategies combine MPC with other control techniques, such as PID, fuzzy logic, or rule-based controllers. These approaches leverage MPC for global optimization and predictive control, while auxiliary controllers provide faster or more robust responses under specific conditions. Hybrid strategies are especially valuable in scenarios requiring rapid switching between modes (e.g., grid-connected to islanded) or managing nonlinearities and uncertainties that MPC alone may not address efficiently [55,56]. Table 6 summarizes representative applications of these MPC strategies from the recent literature, illustrating their practical-use cases, targeted control objectives, and reported performance. The choice of deployment strategy depends on factors such as MG scale, communication infrastructure, computational resources, and desired trade-offs between performance and complexity.

Table 6. Using MPC techniques in MGs.

Ref.	Desired Control Objectives	Advantages	Limitations	Algorithm	Results
[150]	Enhance the efficient use of flexible resources (such as PV panels and battery storage systems) in buildings to reduce operational energy costs.	(1) SMPC is more likely to realize daily cost savings compared to CMPC and SHMPC strategies. (2) SHMPC can achieve higher cost savings in actual operation by aligning the optimization horizon's commencement with the onset of the off-peak period.	(1) SMPC still has higher daily costs than the real-time optimal control strategy for most of the winter season due to low forecast accuracy. (2) There is no one control strategy that is definitely superior to the other strategies under all operating conditions.	CMPC SHMPC SMPC RTC	Hybrid control strategies using RTC in winter and SMPC in other seasons effectively optimize building energy flexibility in subtropical regions.

Table 6. *Cont.*

Ref.	Desired Control Objectives	Advantages	Limitations	Algorithm	Results
[177]	Optimizing the management of power flow among battery ESS involves considering factors such as line losses, voltage constraints, and converter current constraints. Achieving real-time implementation necessitates a significant reduction in computation time.	(1) Fast solution via convex optimization and robust solvers. (2) Handles line losses, voltage, and current constraints. (3) Applicability for real-time MPC in MGs.	(1) The simplified battery model may not fully capture all system dynamics. (2) Assumptions about battery charge and discharge efficiencies may not be universally applicable across all operational scenarios. (3) Approximations inherent to the variable efficiency battery SoC model.	Convex vs. non-convex problems and robust solvers	The convex MPC approach rivals non-convex methods in real-time microgrid simulations, notably cutting computation time while maintaining competitive power loss at 12.638 kW versus 11.596 kW.
[178]	Address the instability problems caused by constant power load (CPL) in DC MGs. Develop a robust and fast-responding controller for DC/DC converters feeding CPLs.	(1) AMPC based on DRL provides robustness and fast response to system dynamics. (2) Deep Q-Network (DQN) strategy adaptively designs the controlling signal coefficient for each variable operation point.	(1) The complexity of the AMPC algorithm (2) The requirement for training data for the DQN model	AMPC with DQN	The AMPC controller successfully resolves instability issues in DC MGs caused by CPL, demonstrating robustness and rapid dynamic response.
[179]	Optimize energy management in MG Balance power generation and demand through ESS Minimize operating costs. Improve MG efficiency. Reduce environmental impacts.	(1) AMPC addresses issues associated with MG. (2) AMPC optimizes power-sharing among DERs while considering physical and operational constraints. (3) AMPC minimizes operating costs and improves MG efficiency.	(1) AMPC requires accurate prediction of disturbances, which can be challenging (2) AMPC is more complex to implement than traditional control algorithms	AMPC based receding horizon control	AMPC proves to be an effective tool for optimizing energy management in MG, reducing operating costs, enhancing efficiency, and minimizing environmental impact.
[180]	Minimize energy costs and maximize renewable energy utilization in MGs. Develop a control scheme that works effectively in both grid-connected and islanded mode.	(1) SHMPC scheme effectively reduces energy costs by 6% compared to non-switched HMPC. (2) SHMPC effectively utilizes renewable energy and storage capabilities under changing grid connection conditions.	(1) No energy demand or production forecasting. (2) Conceptual character, further research needed to implement advanced functionalities.	SHMPC	SHMPC effectively reduces energy costs and maximizes renewable energy utilization in MGs SHMPC is applicable to any standard MG.
[121]	Minimize the operating cost of a MG. Handle the intermittency of RESs and the high stochasticity in market prices and loads.	(1) Imitation learning cuts training time by 17 times compared to a Q-learning (2) Proposed approach achieves an operating cost close to the theoretical minimum value under various uncertainties.	(1) Requires a MILP solver to generate an expert policy. (2) May not be applicable to MGs with complex constraints.	Data-driven online approach based on imitation learning	Proposed data-driven approach efficiently optimizes MG operation costs under uncertainties in both simulated and real-world scenarios.
[181]	Optimize the overall cost of generation in a hybrid MG, taking into account constraints associated with supply–demand balance, capacity, and ramp-rate.	(1) The proposed decentralized algorithm is independent of the initialization stage. (2) Proposed algorithm can handle convex objective functions. (3) The convergence of the presented algorithm is proven via convex analysis and the utilization of the Lyapunov function technique	Algorithm may not be applicable to non-convex optimization problems.	Fully distributed algorithm	Proposed distributed algorithm minimizes MG generation cost while satisfying constraints, with proven convergence.

Table 6. *Cont.*

Ref.	Desired Control Objectives	Advantages	Limitations	Algorithm	Results
[182]	The primary goals of control in this context encompass optimizing economic performance metrics through forecasts of PV generation and load demands, minimizing disparities between planned and actual energy transactions, and ensuring compliance with probabilistic constraints.	(1) Efficient energy management across diverse timeframes. (2) Adaptability to stochastic disruptions and correction of predictive inaccuracies. (3) Improved system-wide efficiency via updates to the overarching plan.	(1) Dependency on precise forecast data for optimal functionality. (2) Complexity in deployment and computational demands (3) Sensitivity to the precision of models and tuning of parameters.	Two-layer	The dual-layer algorithm enhances MG energy management by combining economic and stochastic MPC, with recurrent updates improving system performance.
[183]	Attain concurrent control of frequency and voltage in an HVDC transmission system during converter blocking.	(1) Cooperative control effectively regulates frequency and voltage during HVDC blocking. (2) EMPC diminishes peak and steady-state deviations in frequency and voltage. (3) EMPC outperforms droop control, LQR, and the original system.	(1) Complexity of the EMPC (2) Requirement for accurate models of the HVDC transmission system and wind farm.	EMPC	Proposed EMPC-based cooperative control effectively regulates frequency and voltage during HVDC blocking, outperforming traditional methods.

Based on the findings from the studies in Table 5, the diverse array of algorithms presented in the table demonstrates the versatility of MPC in addressing specific objectives in MG applications. The results highlight the need for a tailored approach, considering the unique advantages and limitations of each algorithm based on the targeted control objectives.

Although most academic works on MPC in MGs use theoretical models or simulation-based validation, more research and industrial pilots are increasingly implementing MPC strategies in practice. Such deployments confirm the practicability of MPC-based energy management systems in real-world applications and provide valuable insight into computational constraints, system robustness, and performance under uncertainty. Table 7 presents an overview of some real-world MPC applications in MGs, identifying their operational setting and presenting findings.

Table 7. Real-world MPC applications in MGs.

Ref.	Scenario	Type of MPC	Hardware/Platform Used	Key Outcomes
[184]	Frequency regulation using DRL in PV–diesel MG	DRL-MPC	STM32-based embedded system	Improved frequency stability under load changes
[185]	Economic dispatch in grid-connected MG	EMPC	Lab-scale OPAL-RT + MATLAB	52.1% cost reduction and smooth DER transitions
[186]	Power sharing across MMGs	DRMPC	Simulink-HIL + TCP/IP network	Enhanced economy and improved data privacy
[187]	CO_2 reduction in islanded MG with PV and battery	Dual-layer EMPC	Raspberry Pi + SCADA interface	10% CO_2 reduction and optimized generator usage

4. Exploring Multi-Objective Optimization Using MPC

4.1. Concept and Benefits

Minimization, voltage stability, frequency regulation, emissions reduction, and energy efficiency must be addressed simultaneously. Traditional single-objective control methods often fall short in balancing these conflicting goals. MPC is a powerful control strategy that can be used to optimize the operation of complex systems [164,188,189]. However, many systems have multiple objectives that may conflict with each other [164]. Multi-objective optimization (MOO) is a mathematical framework that can be used to find solutions that trade-offs between these different objectives [190,191]. MPC can be used to solve MOO problems by formulating the optimization problem as a set of constraints that the MPC controller must satisfy [192,193]. The controller will then find a solution that satisfies all of the constraints and that also comes as close as possible to achieving the desired trade-offs between the objectives [193,194].

MOO using MPC has been applied to a wide range of problems. In the MG management domain, it is employed to optimize operation for cost reduction, maximize renewable energy utilization, and maintain system stability [195,196]. Additionally, in power system operations, MOO with MPC contributes to optimizing the performance for cost, emission reduction, and reliability [197–199]. Furthermore, in building energy management, this method has been beneficial in reducing energy consumption costs, enhancing occupant comfort, and minimizing environmental impacts [49,200]. Moreover, MOO with MPC has several benefits over traditional single-objective optimization approaches [192]. These benefits include the following:

- Improved system performance: MOO can find solutions that are closer to the Pareto frontier, which is the set of all non-dominated solutions [201]. This means that MOO solutions are better at trading off between different objectives [201,202].
- Reduced risk of suboptimal solutions: Single-objective optimization approaches can sometimes get stuck in local optima, which are solutions that are better than any of their neighbors but not as good as the global optimum [203–205]. MOO is less likely to get stuck in local optima because it considers multiple objectives [205,206].
- Increased flexibility: MOO can be used to explore a wide range of trade-offs between objectives, allowing decision-makers to choose the solution that best meets their needs [207,208].

Table 8 compiles research studies on MOO with MPC. The advantages are categorized into three aspects: improved system performance, reduced risk of suboptimal solutions, and increased flexibility. The findings vary across studies, indicating that MOO with MPC can enhance system performance and mitigate suboptimal solutions, but the extent of increased flexibility depends on the specific application. Further exploration and standardization of methodologies are essential for harnessing the full potential of MOO with MPC in diverse domains.

Table 8. Summary of research findings on MOO with MPC.

Ref.	[209]	[210]	[99]	[96]	[211]	[212]	[213]	[214]	[215]	[216]	[217]	[218]	[219]	[220]
Improved system performance	×	×	×	✓	✓	×	✓	✓	✓	×	✓	×	✓	×
Reduced risk of suboptimal solutions	✓	×	✓	×	×	✓	×	×	×	✓	×	×	×	×
Increased flexibility	×	✓	×	×	×	×	×	×	×	×	×	✓	×	✓

4.2. Challenges in MOO with MPC

Despite its advantages, integrating MOO into MPC introduces several technical and computational challenges that can hinder practical deployment in MG environments. One of the primary barriers is computational complexity. MOO problems inherently involve solving multiple objective functions simultaneously, often requiring the evaluation of Pareto-optimal fronts or large-scale optimization under constraints. This leads to significantly increased computational demand compared to single-objective MPC, particularly in real-time or high-frequency control scenarios. For microgrids with limited processing resources, this can compromise responsiveness or scalability [221,222]. Another challenge lies in the definition and quantification of objectives. Many technical and economic goals—such as reliability, user comfort, emissions, or flexibility—are difficult to express in measurable, mathematically tractable forms. Moreover, assigning appropriate weights or prioritization across objectives can be subjective and context-dependent, potentially affecting fairness and consistency in control outcomes. Inaccurately defined objectives may lead to suboptimal or biased control actions that fail to meet system-level goals. A third critical issue is ensuring convergence and solution quality. In complex or nonlinear MG systems, MOO with MPC can suffer from poor convergence behavior or become trapped in local optima, especially when optimization landscapes are non-convex or data-driven models are used. Further, balancing short-term and long-term goals across shifting time horizons adds another level of complexity to solution stability. Robustness of solution quality across shifting system states remains an open research problem [223,224]. For instance, a case study involving the use of a knee point-based evolutionary multi-objective optimization (KBEMO) algorithm shows that traditional methods require selecting one solution from the entire Pareto front at each control interval, which is computationally expensive and necessitates regular human input. By automatically identifying the knee point, the solution with maximum marginal utility, KBEMO reduces computational complexity and minimizes the need for human decision-making, enabling faster and more real-time-appropriate MPC implementation in MG energy management [225].

Table 9 provides an overview of the difficulties associated with integrating MOO and MPC. These challenges encompass heightened computational intricacies, challenges in articulating objectives, and the necessity to manage compromises between multiple objectives. Various research studies shed light on distinct facets of these challenges, underscoring the intricacies introduced by the amalgamation of multiple objectives and the complexities involved in their definition and equilibrium. Effectively addressing these challenges is pivotal for unlocking the complete potential of MOO integrated with MPC across a spectrum of applications, spanning from process control to energy management. Additional research and development efforts are imperative to surmount these hurdles and establish resilient methodologies for proficient multi-objective control employing MPC.

Table 9. The challenge of MOO with MPC.

Ref.	Increased Computational Complexity	Difficulty in Defining Objectives	Trade-Offs Between Objectives
[12]	×	✓	×
[192]	✓	×	×
[213]	×	×	✓
[226]	×	×	✓
[227]	×	✓	×
[228]	×	×	✓
[229]	×	×	✓
[230]	×	×	✓

5. Hierarchical Control Strategies with MOO and MPC in MGs

5.1. Overview of Hierarchical Structures

Hierarchical control in microgrids is a structured approach that divides the control task into three layers: primary, secondary, and tertiary. Each level operates at a different timescale and has different responsibilities. Primary control manages real-time frequency and voltage regulation. It is decentralized and fast-acting, relying on local measurements and droop-based methods to provide grid stability in the short term [231,232]. Secondary control corrects deviations introduced at the primary level. It coordinates multiple DERs to regulate voltage and frequency to their nominal values and ensure power sharing among DERs [233]. Decision-making algorithms at this level aim to optimize power generation, consumption, and storage to minimize operating costs, maximize revenue, and efficiently integrate renewable energy sources [234,235]. Tertiary control acts at the highest level, managing energy exchange between the MG and the main grid or other MGs. It addresses economic optimization, energy trading, and strategic decision-making for cost minimization and market participation [236]. By aligning control responsibilities with system layers, hierarchical control frameworks ensure modularity, scalability, and responsiveness—essential features for modern, distributed MGs, as shown in Figure 6.

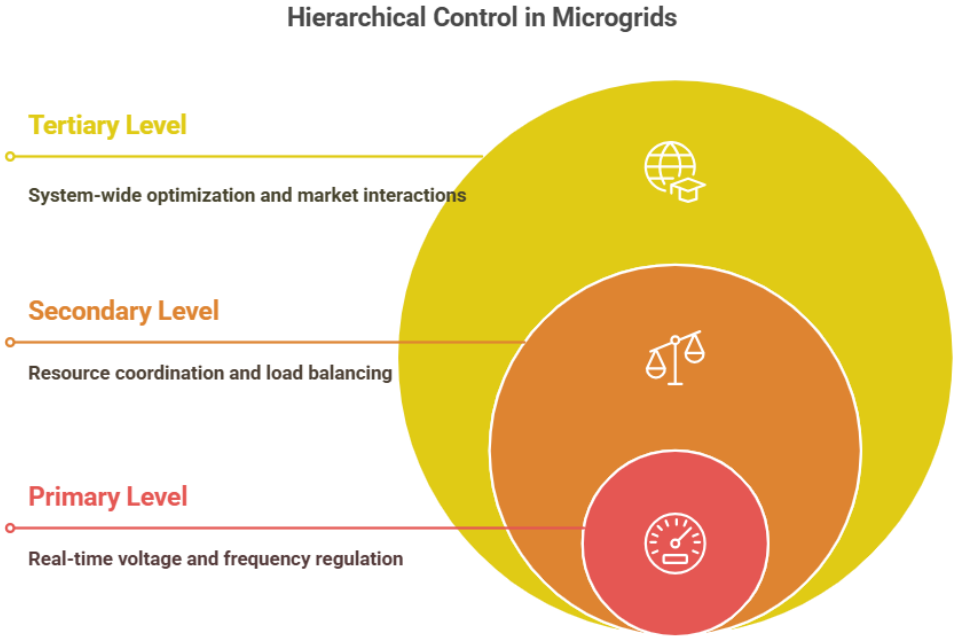


Figure 6. Hierarchical control structure in MG.

5.2. Technical vs. Economic Objectives in MGs

The operation of MGs requires achieving a careful balance between technical performance metrics (voltage regulation, frequency stability, and power quality) [233] and economic objectives (cost minimization, emission reduction, and profit maximization) [234,235]. These objectives often conflict; for instance, minimizing operational costs might reduce reserve margins, thereby compromising frequency stability [237–239]. Integrating MOO with MPC in hierarchical control offers a powerful mechanism to address this tension. At primary levels, MPC ensures technical objectives are met through predictive dynamic control [233], while higher levels use MOO frameworks to optimize economic metrics over longer horizons [237–239]. This layered strategy enables real-time control actions to align with long-term strategic goals, maintaining both grid stability and operational efficiency [29,240].

However, implementing such coordination is complex. It requires accurate system modeling across levels, harmonized control objectives, and careful prioritization of potentially competing goals. This integration becomes even more critical in multi-MGs or under scenarios with frequent mode switching between grid-connected and islanded operation [236].

Integrating MOO and MPC within a hierarchical control framework enables MGs to strike a balance between technical and economic objectives, ensuring efficient and reliable operation. However, it is crucial to note that designing and implementing hierarchical control strategies demands careful consideration of system dynamics, uncertainties, and the interdependencies between different control levels [29,240]. A review of the recent literature reveals a growing but still limited number of case studies that successfully integrate MOO and MPC into hierarchical control architectures for MGs. Table 10 summarizes these studies, highlighting the types of MGs involved, the specific technical and economic objectives targeted, whether hierarchical control was employed, and the inclusion of multi-microgrid coordination. The findings indicate that while many studies address either technical or economic control, few simultaneously address both within a hierarchical structure. Even fewer extend this integration to manage multiple interconnected microgrids. Most research prioritizes cost and energy management, with voltage/frequency regulation either assumed or simplified. This gap suggests a clear opportunity for future work in designing fully integrated, multi-layer MPC architectures that systematically optimize across both technical and economic dimensions in complex MG environments.

Table 10. Examining the landscape of MOO with MPC in MGs.

Ref.	Type of MG	Economical Index	Technical Index	Result	Hierarchical Control	Priority	Multi-MGs
[180]	Not mentioned	(1) The energy cost of the MG (2) The diesel generator fuel cost (3) The energy price from the main grid	(1) power balance equation (2) SoC (3) The voltage levels of the distribution network (4) The operation of the diesel generator	The results show that the proposed SMPC algorithm can achieve significant cost savings while ensuring the reliable operation of the MG.	✓	Economic operation and technical operation	×
[241]	AC hybrid	(1) The cost of energy production (2) The cost of battery degradation	(1) SoC (2) Power limits of the ESS (3) Limitation power of wind turbine (4) Limitation of grid connection power (5) Limitation on power transfer between the ESS and grid	The proposed MPC minimizes energy costs and improves power quality by stabilizing the output of wind turbines. It is suitable for the control of wind/ESS hybrid plants, especially in isolated grids.	×	Economic operation	×
[242]	Not mentioned	(1) The cost of energy purchased from the main grid (2) The cost of energy consumed by the loads (3) The cost of energy stored and discharged by the ESSs	(1) Battery SoC (2) Battery capacity (3) Using RES (4) Grid power import (5) Grid power export (6) Power balance (7) Power quality (8) Voltage level (9) Switching frequency	This paper used a hybrid constrained CPSO-MPC algorithm. The findings show that the proposed MPC system can reduce the energy-generation cost and improve power quality by decreasing the power-output oscillations in wind farms.	×	Economic operation and technical operation	✓
[243]	AC/DC hybrid	(1) Cost of energy not served (2) Net present value (3) Levelized cost of energy (4) Payback period (5) Benefit-to-cost ratio	(1) Energy balance error (2) Hydrogen balance error (3) Voltage deviation (4) Frequency deviation (5) SoC	The results revealed that the proposed multistage energy and power management policy for a hybrid MG with photovoltaic and hydrogen storage was efficient in energy management, economic reduction, and environmental sustainability. The proposed policy includes three stages: day-ahead, real-time, and emergency.	×	Economic operation	×

Table 10. *Cont.*

Ref.	Type of MG	Economical Index	Technical Index	Result	Hierarchical Control	Priority	Multi-MGs
[244]	AC/DC hybrid	(1) The cost of energy purchased from the main grid (2) The price of energy sold to the main grid (3) The cost of operating the converters	(1) Power flow (2) Voltage magnitude	Simulation results indicated that the suggested algorithm enhanced the overall system performance with its faster response, improved power sharing, and stable bus voltages in comparison to traditional control techniques.	×	Technical operation	✓
[245]	Not mentioned	The cost of electricity	(1) Power flow (2) SoC	The paper presents an optimal MPC in two stages for hybrid ESSs that smooths wind fluctuations and load-demand variations, enhancing stability and reliability.	×	Economic operation and technical operation	×
[246]	Not mentioned	(1) Fuel consumption (2) Power purchase from the main grid (3) Renewable energy curtailment	(1) Balance between active and reactive power (2) Voltage magnitude (3) Current magnitude (4) SOC of ESSs (5) Ramp rate limits for PV and diesel generators	This study proposes a HEMPC strategy for MG in islanded and grid-connected modes, considering economic factors and weather prediction. Simulations confirm minimized cost and enhanced utilization of RESs.	×	Economic operation	×
[247]	Not mentioned	(1) Operation cost (2) Investment cost (3) Income from selling excess power	(1) Hydrogen storage level (2) Load demand (3) Security of hydrogen	This paper discussed an improved MPC-based scheduling approach for cost-effective and robust hydrogen-based MGs, considering hydrogen facility security constraints. Results confirm the effectiveness of the scheme in offering cost-effective and reliable MG operation.	×	Economic operation	✓
[248]	AC/DC hybrid	(1) Diesel fuel cost (2) Battery replacement cost (3) Diesel generator maintenance cost (4) RESs cost (5) Power purchased/ sold cost (6) MG total cost	(1) Frequency (2) Voltage deviation (3) Load balancing (4) Load factor (5) THD (6) RESs Factor (7) SOC (8) Total system losses	This study proposes an optimal load management approach based on finite control set MPC for a wind–solar islanded hybrid AC/DC MG to achieve minimum operating cost with a guarantee of power supply to the critical loads. The results demonstrate that the method successfully decreases cost and provides a reliable power supply.	×	Economic operation	×

However, there is currently no established standardization framework for hierarchical control, particularly for multi-MG environments. Protocol convergence, layer synchronization, and coordinated control policies are key areas that future research needs to address to enable interoperability and scalability.

6. Integration of MPC Within Hybrid Control Strategies

Hybrid control methods that combine MPC and other control strategies have gained growing interest in recent years, especially for complex systems such as MGs [55,56]. These approaches aim to use the advantages of various control methods to improve performance and reduce difficulties caused by complex system dynamics and constraints [249,250]. MPC is a widely used control approach that has the benefit of controlling complex dynamics and constraints, but it can be computationally demanding and less effective for fast-changing systems [251,252]. Other control approaches, such as proportional–integral–derivative (PID) controllers, are simple and robust, but can struggle with complex optimization

problems [253,254]. By combining MPC with other control techniques, hybrid control techniques attempt to overcome the drawbacks of the individual techniques and enhance overall performance [255–257]. MPC can address the complex optimization facets of the system, while other control methods present quicker response or manage some of the system constraints [256,257]. Several hybrid control techniques have been investigated for MGs and other sophisticated systems. Some of the popular techniques are as follows:

- MPC-PID hybrid control: This strategy combines MPC with PID controllers, utilizing MPC for overall optimization and PID controllers for faster response to disturbances [258]. In Reference [259], a novel path-tracking controller is proposed for autonomous vehicles, combining kinematic MPC, PID feedback control, and a vehicle sideslip angle compensator. The controller significantly improves tracking performance at both low and high speeds, effectively handling disturbances and uncertainties. Reference [40] analyzes interlinking converter control in hybrid AC/DC microgrids, summarizing the current state of research and development in control structures, strategies, and techniques. It highlights the strengths and limitations of existing approaches and outlines future directions. In Reference [260], a novel cooperative PSO-based method is proposed for tuning quadrotor trajectory-tracking MPC parameters, enhancing tracking performance and robustness compared to other tuning approaches. The hybrid control strategy combines MPC for position control and PID controllers for attitude control.
- Hierarchical control: This approach employs a hierarchical structure, with MPC at a higher level, handling long-term optimization, and other control techniques at lower levels, managing specific subsystems or fast-changing dynamics [258]. A hybrid control strategy is proposed for a hybrid AC/DC MG, combining low-level, intermediate-level, and high-level control to achieve bus voltage stabilization, ancillary service provision, and power-sharing and frequency-stability improvement. The adaptive virtual inertia outperforms traditional linear controllers in terms of frequency stability [261]. Hierarchical control is a crucial methodology for managing MG complexity, enabling reliable, efficient, and stable operation under various conditions. This layered control structure optimizes MG performance, coordination, and adaptability in both normal and islanding modes [262]. The proposed enhanced MG power flow (EMPF) algorithm accurately incorporates hierarchical control effects, improving power flow analysis and monitoring, especially for complex urban MGs [263].
- Switching control: This strategy dynamically switches between different control techniques based on system conditions. For instance, MPC may be used during normal operation, while PID controllers take over during transient disturbances [258]. An enhanced switching control strategy utilizing droop control and disturbance observer effectively mitigates transient disturbances and ensures seamless and stable operation of AC/DC hybrid MGs during grid-connected and island-mode transitions [264]. In Reference [265], a hybrid smart MG employing intelligent fuzzy control, PID/PI controls, and switching control effectively manages PHEV charging, optimizes renewable energy utilization, and ensures system stability for V2G and G2V operations.

Employing hybrid control strategies brings forth a host of advantages in contrast to conventional single-control approaches. These benefits encompass improved performance, as hybrid control can effectively capitalize on the strengths inherent in various control techniques [266,267]. Additionally, hybrid control affords enhanced flexibility, allowing for adept adaptation to diverse system conditions and constraints [266,268]. Moreover, there is a notable reduction in computational burden, as hybrid control methods can alleviate the workload on MPC by delegating specific tasks to other complementary control techniques [266,269].

In the MG context, hybrid control strategies have proven effective across various facets of MG operations [270], notably in energy management. These strategies optimize energy generation, storage, and consumption to minimize costs, maximize the utilization of renewable energy, and ensure system stability [270,271]. Another important application is voltage regulation, where hybrid control strategies work to maintain voltage levels within acceptable ranges. This regulation is vital to prevent equipment damage and uphold the overall quality of power within the MG [270]. Furthermore, these hybrid strategies have a fundamental role in the reduction of power quality issues. By managing power qualities like harmonics, flicker, and sags, they ensure smooth and reliable operation of sensitive loads in the MG [270,272].

Moreover, hybrid approaches are important in the implementation of demand-response programs by managing energy consumption based on grid conditions or market signals [270]. Lastly, in islanding and restoration applications, these strategies allow for easy switches from grid-connected to islanding mode and an efficient restoration upon reconnecting with the main grid [270].

7. Discussion

This study emphasizes the vital role of MPC as the most suitable choice for MG control.

MPC is an effective control approach to MGs, with outstanding enhancement in reliability, environmental aspect, efficiency, and economic operation [273]. Several case studies and practical implementations, such as those presented in Table 7, support the theoretical discussion by highlighting real-world implementations of MPC in MGs. These studies offer valuable insights into the algorithm's performance under fluctuating operating conditions and dynamic constraints. The ability of MPC to handle complex dynamics and constraints, and its multi-objective nature make it well-suited to the complexity of MG operation [60]. Moreover, the adaptability of MPC enables it to adjust to different MG setups and objectives, establishing it as an adaptable tool for optimizing MGs [274]. Notably, MPC supports various MG setups, including RESs, efficient management of energy storage systems, and optimization of demand-side response [275]. MG management has discovered a dependable solution in MPC, showcasing adaptability by effectively addressing diverse objectives and managing nonlinearities.

A thorough examination of various algorithms employed in MG scenarios reveals the need for a proper method based on specific control objectives [276]. The present study emphasizes the important role of selecting the most suitable algorithm for specific control objectives, thus enhancing management effectiveness in MPC for MGs, as shown in Tables 4 and 5. Table 4 offers a thorough comparison of diverse MPC algorithms, delineating crucial aspects, including system dynamics, objective function, optimization problem, computational complexity, and applications. Understanding the details of these algorithms is indispensable for researchers and engineers, as it enables informed decision-making in control-system design and optimization.

Ensuring optimal and dependable network performance in MGs necessitates addressing both technical and economic objectives with equal significance. However, these objectives may conflict with each other, so this study examines the combination of MOO using MPC in MGs. The fusion of MOO with MPC presents an opportunity to enhance system performance and mitigate suboptimal outcomes, as evidenced in Table 8. Nonetheless, despite the advantages of this integration, it is imperative to acknowledge and address the accompanying challenges outlined in Table 9. Consequently, the incorporation of MOO, using MPC, into a hierarchical control framework empowers MGs to strike a harmonious equilibrium between their technical and economic objectives, fostering efficient and reliable performance, as detailed in Table 10. Notably, Table 10 indicates the limited development of

hierarchical control combined with MOO, using MPC in MGs. This issue underscores the need for researchers to prioritize the application of hierarchical control methods in order to effectively address both the technical and economic challenges of MGs. Additionally, the lack of effective implementation of hierarchical controllers in managing various MGs highlights the importance of using more interconnected and coordinated control strategies.

Moreover, MPC is one of the most widely used control methods that has gained immense popularity due to its high performance in stabilizing complex dynamics and constraints. However, its computationally intensive nature can provide difficulties in rapidly changing systems. Hybrid control strategies present a valuable alternative by integrating MPC with other control methods within complex systems such as MGs. Such strategies focus on utilizing the strengths of various control methods to improve performance while managing the complexities caused by dynamic behavior and operational constraints.

This research emphasizes the importance of customized solutions because generic solutions fail in real-world scenarios. The efficiency of MPC depends on matching with a particular set of control objectives. Therefore, ongoing research and standardization of procedures are essential for the full realization of MOO through MPC in both hierarchical control strategies and hybrid control strategies across various MGs. In addition, several strategies are combined to create higher management efficacy in MGs that utilize MPC. This strategic integration is important, as it allows MGs to enhance performance potential while effectively managing their diverse and sometimes conflicting objectives.

Considering the rising incidence of cyber–physical attacks on the power grid, MPC's predictive architecture offers inherent advantages in terms of fault tolerance and robustness. By continuously optimizing control actions based on predicted data, MPC can respond quickly to anomalous system behavior, such as data spoofing or actuator failure. Furthermore, DMPC architectures encourage cybersecurity by decentralizing control logic, reducing the attack surface associated with centralized systems.

Practical Barriers and Scalability Challenges

While MPC has shown remarkable potential in improving MG performance, several real-world challenges limit its widespread adoption. A major issue is the scalability of the DMPC architecture in large-scale or networked MG environments. As the number of agents increases, computational load and communication overhead grow significantly, particularly when continuous coordination among subsystems is required. In such settings, ensuring convergence and real-time responsiveness becomes increasingly difficult, especially in the presence of asynchronous update mechanisms or limited communication bandwidth.

Another essential challenge relates to the sensitivity of MPC to prediction accuracy. MPC depends heavily on predicted inputs, such as load profiles, renewable generation, and price signals, to determine optimal control actions. However, forecasting models inevitably involve uncertainty, and inaccuracies in predicted values can spread through the optimization process, leading to suboptimal or even unstable control actions. This challenge is particularly severe in MGs with high renewable integration, where short-term variability and weather-related fluctuations are common.

Moreover, the complexity involved in implementing MPC, especially for nonlinear and mixed-integer systems, presents a major limitation for real-time control. The high computational demands restrict the use of advanced MPC forms (like MOMPC, EMPC, and RMPC) on low-processing-capability systems, such as embedded controllers in MGs. Therefore, theoretical advancements often fall short of practical implementation.

8. Future Research Direction

First and foremost, the research community is placing significant emphasis on the development of advanced MPC algorithms specifically designed for MGs [58,277]. This effort goes beyond refining existing algorithms, aiming to develop novel methodologies that prioritize robustness and adaptability to the unique dynamics and complexities inherent to MGs. This involves exploring innovative approaches to enhance the predictive capabilities of MPC, ensuring more effective anticipation and response to dynamic changes in MG operations while maintaining stability and reliability.

In addition, there has been a concerted effort to integrate advanced optimization techniques, such as artificial intelligence, machine learning, and deep learning, into MPC approach to strengthen their performance and flexibility for managing MGs under different conditions [278,279]. Integrating MPC with these intelligent optimization techniques presents a valuable direction for optimizing MG performance and addressing emerging concerns of the modern energy system. However, this combination remains underexplored in current research.

Moreover, future research should focus on resolving real-time deployment issues, enhancing interoperability with renewable forecasting models, and integrating AI-based learning enhancements into MPC frameworks.

In addition, there is a critical need for the real-time implementation of MPC in MG configurations [280,281]. This is essential because the system needs to address the challenges associated with dynamic and rapidly changing conditions common in MG operations. Real-time applications of MPC enable MG controllers to continuously monitor the system data, update future projections, and adjust control actions based on altered conditions, ensuring maximum performance and stability. Real-time implementation of MPC in MGs can be gained by advancements in computing power, sensor technology, communication networks, and control algorithms.

Another critical area of research is to apply MPC to large-scale MGs and transactive energy systems, and how to deal with the unique challenges posed by their size and complexity. MPC has to be scaled up to manage heterogeneous and interconnected systems and enable system-wide optimization. Scientists are actively working on how to customize MPC to suit the distinct characteristics of large-scale MGs and transactive energy systems while considering network topology, grid dynamics, and market dynamics [282]. More studies are needed to fully unlock the potential of MPC in this field.

Lastly, the research community is committed to conducting more meta-analyses to synthesize existing results, uncover insights, and identify new trends in MPC applications for MGs. This effort aims to provide a comprehensive understanding and drive continuous advancements in MG control methods. The increased focus on developing MPC results from the dedication of researchers to continually advance control theory and pave the way for more cost-effective and resilient MG management. Figure 7 is a graphical overview of the major future research directions of MPC in MGs.

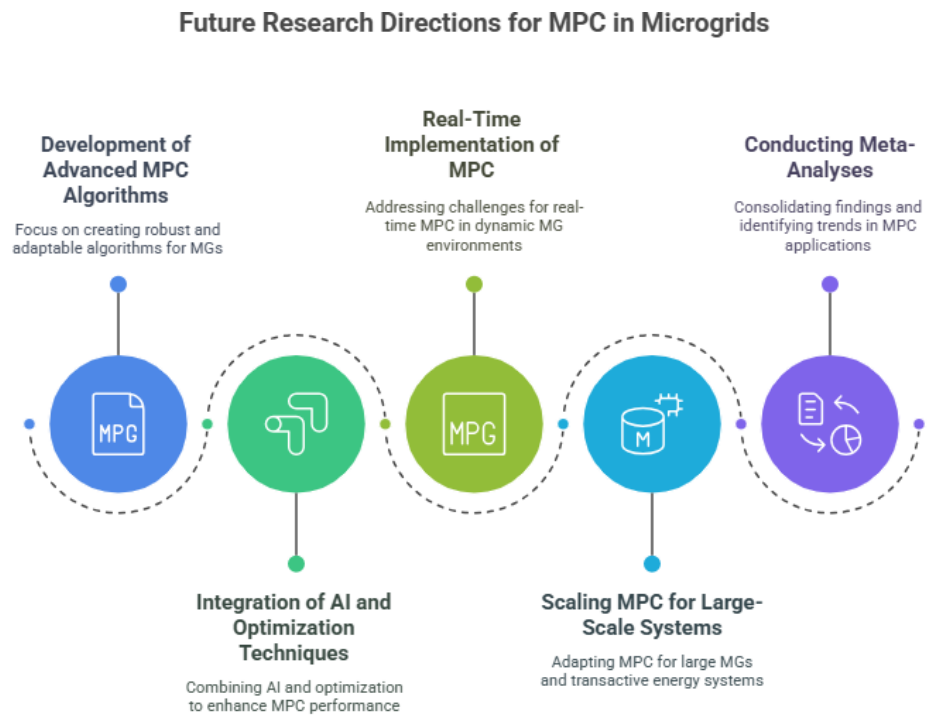


Figure 7. Visual overview of key future research directions for MPC in MGs.

9. Conclusions

MPC is a stable control method for MGs and provides a comprehensive solution to address issues in modern power systems. Its optimal operation of MGs, while considering reliability, environmental effect, efficiency, and economy, makes it a significant factor in enhancing the overall efficiency of MGs. According to this study, one of the key issues in applying MPC in MGs is the tendency of researchers to prioritize either technical or economic considerations over others. Such narrow consideration limits the utilization of hierarchical controllers to control multiple MGs efficiently. Furthermore, prioritizing the selection of the most suitable algorithm based on the objective of the controller in MPC is essential for researchers to achieve their goals more effectively. Certain algorithms are adept at handling nonlinear systems, while others excel in managing linear ones or optimizing multi-objective control. By careful consideration of computational complexity, applicability, and objective function, researchers are able to make informed decisions to ensure implementation of a stable and robust system.

The analysis of various algorithms applied in MG scenarios highlights the essential nature of customizing approaches based on specific control objectives, necessitating ongoing exploration and standardization of methodologies for unlocking the full potential of MOO with MPC across diverse domains. However, the integration of MOO and MPC underscores the complexity introduced by amalgamating multiple objectives. This study emphasizes the imperative nature of overcoming these challenges to seamlessly integrate MOO and MPC across diverse applications.

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