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SURVEY

Model Predictive Control Strategies in Microgrids: A Concise Revisit

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ABSTRACT The world is rapidly integrating renewable energy resources into the existing grid systems. However, the unpredictable nature of renewables and uncertain load profiles cause issues such as poor power quality, lower system reliability, complex power management, battery degradation, high operating costs, and lower efficiency. Microgrids can help smart grid technology overcome several problems associated with renewable energy integration. Distant locations can obtain electricity without building extensive transmission infrastructure, cutting development costs, or transmission losses. The intermittent nature of renewable energy sources contributes to microgrid problems such as poor power quality, decreased reliability, and high operating costs. Model predictive control (MPC) is an effective method to address challenging industrial and scientific issues. Advancements in MPC that accept different system constraints have solved multiple concerns in uncertain microgrid systems. MPC applied to three hierarchal control layers in a microgrid resolves the problems of power quality, power sharing, energy management, and economic optimization. This study demonstrates that MPC microgrid control is suitable for low-cost operation, improved management, and reliable control. The shortcomings of recent model predictive control techniques for microgrids are reviewed, and future research directions for MPC microgrids are identified.

INDEX TERMS Microgrids, renewable energy resources, model predictive control, power quality enhancement, energy management system, hybrid energy storage system, demand side management, demand response, distributed systems.

NOMENCLATURE

Acronyms

MPC	Model Predictive Control.
RER	Renewable Energy Resources.
ESS	Energy Storage System.
HESS	Hybrid Energy Storage System.
PCC	Point of Common Coupling.
EV	Electric Vehicles.
DMC	Dynamic Matrix Control.
GPC	Generalized Predictive Control.
EPSAC	Extended Prediction Self Adaption Control.
PFC	Primary Frequency Control.
MAC	Model Algorithmic Control.
FSC	Finite Set Control.
CCS	Continuous Control Set.
DSM	Demand Side Management.
DR	Demand Response.
PFR	Primary Frequency Response.
DFIG	Doubly Fed Induction Generator.
BMS	Battery Management System.
SMES	Superconducting Magnetic Energy Storage.
SOH	State of Health.
MC	Microgrid Cluster.
LPV	Linear Parameter Varying.
FTC	Fault Tolerant Control.
HMPC	Hierarchal Model Predictive Control.

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I. INTRODUCTION

The scientific community is working to substitute fossil-fueled energy resources with renewable resources. The targets are to reduce environmental pollution, develop a sustainable energy source, provide low-cost electricity, lower oil dependence in developing countries, and provide people with jobs. Traditional energy generation methods are easily controllable and adaptable to user demands. However, renewable energy resources operate intermittently with uncertain load profiles. The high-level penetration of renewable energy resources (RERS) into the national grid may cause energy imbalances and power quality issues [1]. Over the past few years, researchers have addressed these issues. One of the suggested methods uses energy storage systems (ESS) including batteries, capacitors, and flywheels. It can overcome the reliability problems in power systems and offer a continuous source of electricity. With the incorporation of various energy generation systems, ESS have time delays, energy management issues, and high operating costs. Hybrid energy storage systems (HESS) combine multiple energy storage techniques [2]. A good control strategy selects an appropriate ESS to reduce the operating costs, improve time responsiveness and system autonomy.

Modern power systems require dividing the grid into smaller, more manageable units with bidirectional power flow. Microgrid technology may improve power quality and reliability by splitting a grid system into smaller electrical networks. A microgrid contains renewable energy resources, energy-storage systems, local generators, EV chargers, and residential or commercial loads. A grid-connected microgrid can run in islanded mode or concurrently with the main grid using a point of common coupling (PCC) [3]. Both modes of the microgrid require voltage and frequency regulations. An efficient microgrid control system is required to manage the power exchange with the main grid and optimize the operating costs. Consequently, the microgrid behaves as a controllable system that responds to appropriate control signals. Disturbances or faults cause it to switch to the islanded mode to ensure the continuity of supply to local loads. [4]. Figure 1 recreated from [3] illustrates a microgrid with different storage systems and distributed generators connected to the point of common coupling (PCC) by power converters.

A microgrid system can introduce bidirectional power flow during low-voltage operations and cause complications in the protection system. The transitions between islanded and grid-connected modes can introduce local oscillations and stability issues [5]. The intermittent nature of renewable energy sources leads to operational uncertainties. Damping oscillations, voltage, and frequency regulation are necessary for a sustained operation. Droop control methods are popular for power handling in microgrid systems. Droop control avoids critical communication links between different DG's. Frequency-deviation issues and poor dynamic performance are challenges in droop control. Hence, the hierarchical control of microgrids was developed to address multiple performance issues. It is a three-layer structure in which each layer is responsible for addressing specific grid issues.

The model predictive control technique conveniently accommodates physical constraints such as storage capacity and power limits. It addresses microgrid control issues well because it has a feedback mechanism for minimizing system disturbances. [6]. Multi-objective functions can optimize various physical constraints, improve dynamic performance, and provide robust control [7]. MPC techniques, such as dynamic matrix control (DMC), generalized predictive control (GPC), extended prediction self-adaptive control (EPSAC), predictive functional control (PFC), model algorithmic control (MAC), and finite set control (FSC) manage several grid issues. These techniques can handle the intermittent behavior of renewable energy resources, non-uniform demand, sudden load disconnection, and complex geographical distribution of resources [8].

This study presents the utilization of MPC techniques in different control layers of a microgrid. Reliability and controllability issues exist in microgrids with various renewable energy resource (RER) integration. The interconnection of many systems may cause frequency deviations, instability, and frequent outages [9]. Dedicated MPC strategies are required at each microgrid control layer to address the specific problems of power quality, energy management, and economic optimization. To enhance the performance of a microgrid, MPC can be combined with complex methods like fuzzy logic or artificial neural networks [10]. Various efficient MPC approaches, including distributed MPC, adaptive MPC, fault-tolerant control schemes, stochastic MPC, continuous control set MPC, and finite control set MPC, have been developed for reliable and efficient operation of microgrids [11].

With the integration of advanced RER technologies such as offshore wind islands, hydrogen, biomass, and tidal energy, the development of sophisticated control strategies is necessary. Future microgrid structures will need to address the flaws in the current control strategies. This study analyzes the application of model predictive control (MPC) techniques to different control levels of microgrids. Power quality enhancement was explored using finite and continuous control-set strategies. Various MPC energy management techniques have been explored, including the autoregressive integrated moving average algorithm (ARIMA), hierarchical model predictive control, scenario-selected optimization, and reserve strategies. Economic optimization was analyzed using demand-side management (DSM) and demand response (DR) in the tertiary control layer. The performance of different MPC approaches was evaluated in terms of fault tolerance, computational burden, reactive power balance, power sharing, and controller stability. Future work for improved model-predictive control of Microgrids is proposed while existing flaws are analyzed.

Section II explains model predictive control for microgrids. Section III describes different features of microgrid control layers. Section IV elaborates MPC based power quality enhancement in microgrid primary control layer. Section V

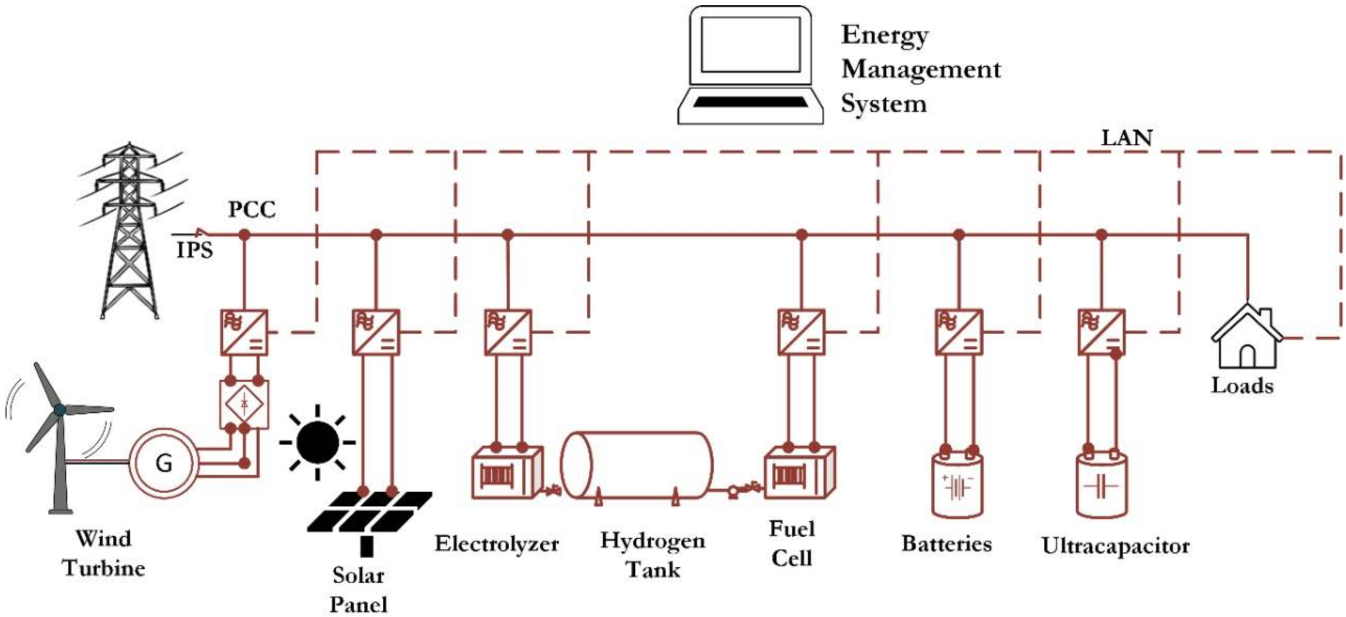

FIGURE 1. An example of a microgrid.

discusses MPC based power sharing in microgrid secondary control layer. Section VI illustrates MPC based economic optimization in microgrid tertiary control layer. Section VII demonstrate future scope of work. Finally, section VIII concludes the findings of this research work.

II. MODEL PREDICTIVE CONTROL FOR MICROGRIDS

Model Predictive Control involves techniques that optimize specific system constraints and minimize the multi-objective cost function [12]. MPC can be used in microgrids at the converter and grid levels. Typically, the former generates switching signals to operate power converters while the latter establishes dispatching instructions for DGs and controllable loads. However, based on the standard MPC architecture, these two layers share comparable control structures and design processes. The core concept of MPC is to forecast the behavior of a controlled system over a specified time horizon. The optimum control input is calculated to minimize a predefined cost function, while guaranteeing that the state constraints of the system are satisfied. Specifically, the control input is calculated by solving a finite-horizon open-loop optimal control problem at each sampling instant. The first portion of the resulting optimal input trajectory is then applied to the system until the next sampling instant, at which point the horizon is shifted and the entire process is repeated.

Figure 2 recreated from [13] shows a block diagram of the model predictive control. The three main processes of control structure development are the design of a predictive model, the development of the cost function, and algorithm-based problem solving. As shown in the figure, the cost function contains constraints. Forming constraints for all physical components can effectively improve system performance, as they can operate optimally within the constraint boundary. The MPC techniques were applied at the microgrid converter and grid levels. The former generates signals for power converters, whereas the latter provides dispatching instructions for distributed generators [14]. The grid-level MPC regulates power flow within the microgrid and battery energy storage system (BESS) [15]. The MPC algorithm predicts future states based on present and prior states. The forecasts serve as input data for the cost function and best command over a particular time horizon computed for all system components. The state outcomes were updated using a cost function. [16]. All available states were updated for the subsequent period, and optimization was performed [18]. Uncertainties were reduced using a receding prediction horizon and feedback mechanism [17].

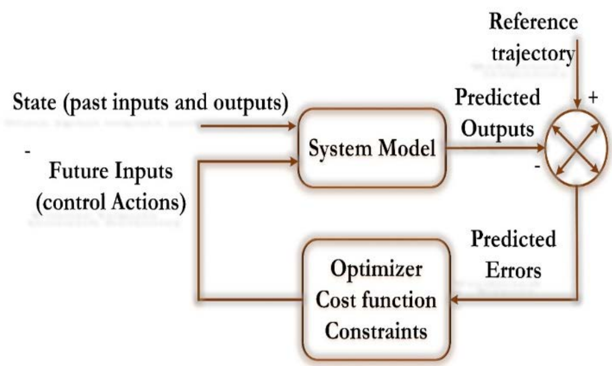

FIGURE 2. Block diagram of MPC.

A. DISTRIBUTED MPC APPROACHES IN MICROGRID CLUSTER

The renewable energy output is unpredictable, which presents difficulties for microgrids. Stochastic MPC (SMPC) techniques, including stochastic programming, scenario-based

MPC, and analytical-based MPC, are used to forecast future renewable energy generation. Polimeni et al. designed and experimentally verified a multilevel energy management system for autonomous Microgrids based on stochastic model predictive control and had the lowest operational cost [19]. Jiao et al. created an effective online dispatch system for a microgrid with an electric vehicle (EV) charging station. It combines stochastic and robust model predictive control for reliable economic optimization. This system has high computational efficiency and minimal operating expenses [20]. Wei et al. developed an improved stochastic model predictive control approach for interconnected energy systems. It is based on a single-layer, multi-timescale framework with cost-effective operation, improved robustness, and enhanced computational efficiency [21]. Each microgrid is a subsystem that operates using a local MPC controller in a microgrid cluster. These subsystems are connected for information exchange [22]. When the states of neighboring systems are connected, the predicted state should be transmitted such that each controller knows the dynamic behavior of its neighbors [23]. The coupling of microgrids may be fully connected, which has a complex infrastructure and is limited to a small number of systems, or partially associated, which is more practical with many subsystems. The former provides complete information sharing with neighbors, whereas the latter is limited to a subset of others [24], [25]. Communication among subsystems may be serial or parallel. In the former method, all the control agents compute simultaneously and transmit information synchronously. In the latter, an order is established among the subsystems, and information is transmitted sequentially [26]. MPC controllers may utilize cooperative or non-cooperative strategies by considering an optimized objective function. In a non-cooperative approach, local controllers optimize a local objective function to develop a Nash equilibrium [27]. The cooperative strategy optimizes the global objective function of each local controller.

III. MICROGRID CONTROL LAYERS

A microgrid has three control layers: primary, secondary, and tertiary layers. The primary control layer addresses power quality concerns; it maintains the voltage and frequency of the microgrid within predefined limits under abnormal loading conditions. The current and voltage setpoints for the RES connected to the microgrid are continually monitored [28]. AC microgrids use voltage source inverters (VSI), whereas DC microgrids use DC-DC power converters to connect different components. These converters were connected in parallel via an AC or DC bus. The instantaneous mismatch between the required and scheduled powers is compensated at the primary level using a popular method known as droop control [29]. Although it is a reliable and flexible technique, it does not perform well under nonlinear load conditions such as harmonic currents.

In addition, the frequency and amplitude vary according to the load. The secondary control layer is responsible for real-time power management. This compensates for the variations caused by the primary control layer, ultimately restoring voltage and frequency [30]. The scheduling of the tertiary control layer determines the operation of the secondary control layer. A secondary control layer controls the electricity exchange between the RES and the external grid.

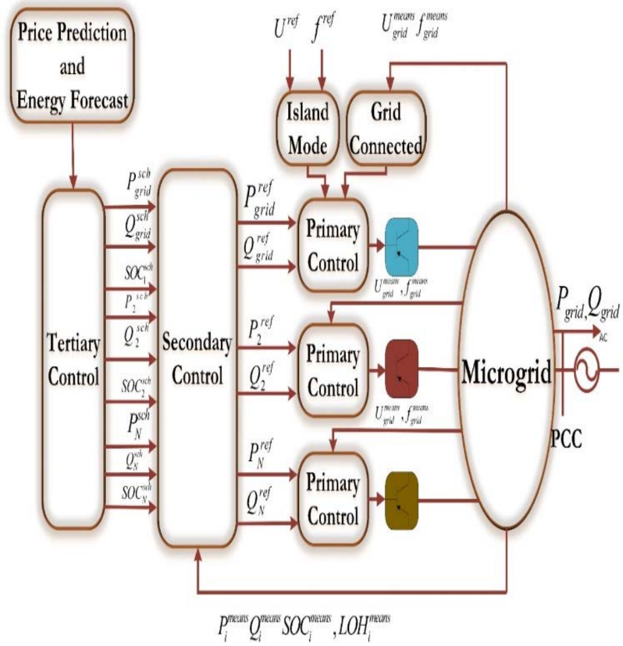

FIGURE 3. The functionality of hierarchal layers in a microgrid.

Figure 3 recreated from [33] shows three hierarchical control layers in a microgrid; the primary control layer receives input data from the secondary control layer and external grid. Power converters maintain voltage and frequency in a microgrid. The primary control layer is responsible for controlling power converters. The tertiary control layer uses price prediction and energy forecast data and provides information regarding the secondary control layer's active power, reactive power, and state of charge.

Any frequency or voltage variation caused by a system disruption should be adjusted to zero. The voltage and frequency amplitudes were continually monitored by the primary control layer. The controllers provide correction signals to ensure equal power distribution among the scattered generators [31]. The tertiary control layer supervises the economic optimization of the microgrid [32]. Forecast, economic degradation, environmental concerns, and operational expenses are employed to develop generation and storage schedules. The secondary control layer obtains the energy management schedule and implements real-time power sharing.

Figure 4 recreated from [33] shows the analogies of the microgrid control hierarchy with four-level control in the process industry. Planning and scheduling are handled at the top level, real-time optimization and enhanced supervisory control are handled at the two inner levels, and regulatory control is handled at the bottom level. The process analogies with the microgrid control layers are represented by the arrows.

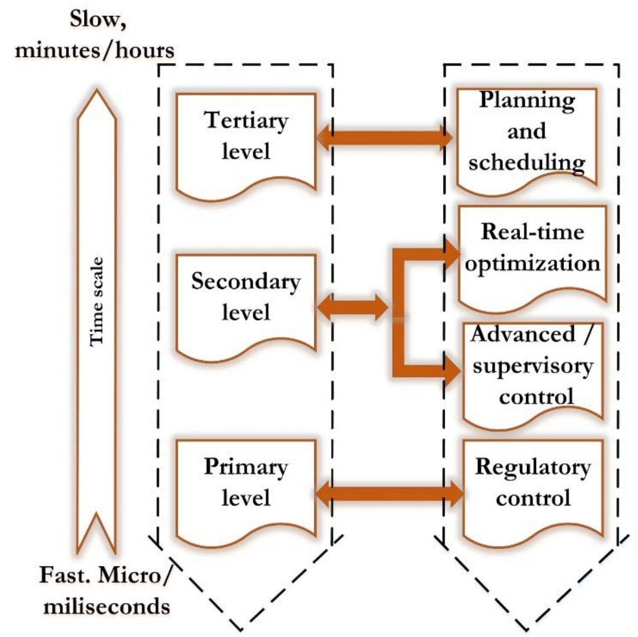

FIGURE 4. The resemblance of microgrid control layers with the process industry.

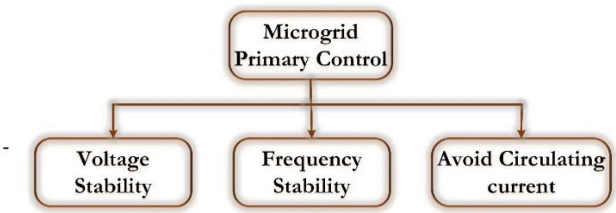

FIGURE 5. A Block diagram of microgrid primary control.

IV. MICROGRIDS PRIMARY CONTROL: MPC-BASED POWER QUALITY ENHANCEMENT

Power quality is an important consideration in the design of microgrids. The microgrid must provide voltage and frequency without any deviations. Any distortion in the output power characteristics, such as voltage, frequency, or amplitude, may result in divergence from electricity market standards. Model predictive control regulates microgrid power converters in grid-connected or island modes to enhance power quality [34]. Figure 5 recreated from [35] shows that three main functions of microgrid primary control are voltage stability, frequency stability and avoiding circulating currents.

The primary control layer monitors the current and voltage set points of the Distributed Generator inside the microgrid. The secondary control layer in the microgrid compensates for voltage and frequency variations induced by the primary control layer. The primary control layer frequently employs the droop-control approach. This technique assigns a characteristic droop to each microgrid inverter. A secondary control layer can resolve the active/reactive power coupling issue of the droop control of the primary control layer [36].

MPC is an attractive option for controlling power converters. The cost function can include several criteria for optimizing switching losses, amount of commutation, total harmonic distortion, and ripple elimination [37]. The prediction horizon length influences converter behavior. A longer interval can improve stability, reduce distortions, and boost efficiency. Additional calculations are required for each sampling interval, thereby increasing system complexity [38], [39]. The computational complexity of MPC-controlled power converters is reduced using different methods, such as multiparametric quadratic programming and linear programming. This process transforms the MPC controller into a piecewise affine controller (PWA) [40]. This strategy is helpful in the development of an explicit MPC in which a fast response can be easily achieved for a larger bandwidth. There are two primary categories of predictive control methods for power converters: finite control set MPC (FCS-MPC) and continuous control set MPC (CCS-MPC)

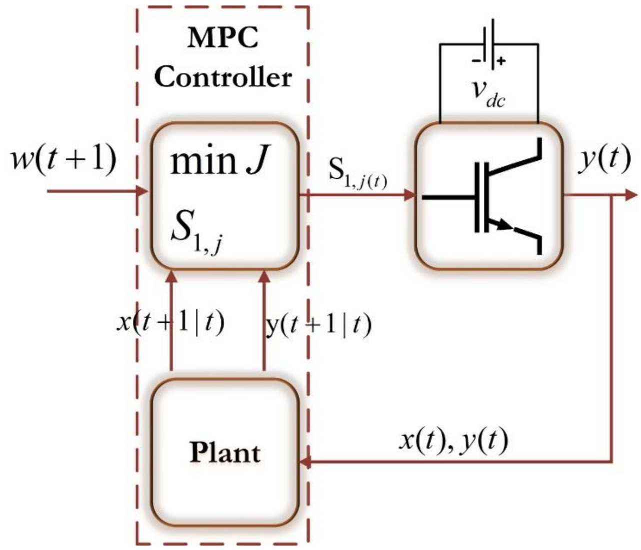

FIGURE 6. A Block diagram of FCS MPC.

A. FINITE CONTROL SET MODEL PREDICTIVE CONTROL (FCS-MPC) OF MICROGRIDS

The coordination of energy storage systems and renewable energy sources is challenging. The ideal solution to this control issue is to operate the FCS-multivariable MPC. The FCS-MPC simplifies the management of power electronic converters in microgrids. It adopts a reduced prediction set and restricts the decision variable to a finite set. Calculating the cost function for each control-action value and selecting the optimal value simplifies the power converters and drive methods. Figure 6 recreated from [41] shows a block diagram of the FCS MPC, where the cost function is optimized for tracking the desired reference w(t+1). The power converter provides feedback to the plant to adjust for system disturbances. Using FCS-MPC in a power converter results in the most efficient and cost-effective switching sequence.

Zhao et al. proposed a modified decentralized finite control set model predictive control (FCS-MPC) system for distributed energy resources (DERs). They combined a power droop controller with a model predictive controller. The proposed control strategy can suppress harmonics under unbalanced MGs and nonlinear load conditions. This can reduce the amount of negative-sequence fundamental reactive power more efficiently [41].

Khan et al. suggested a cost function with two objectives: maintaining the output voltage and load current under these conditions. The two-step horizon prediction approach minimizes the switching frequency and computational overhead. In contrast to conventional controllers, their study demonstrated superior steady-state performance, lower computational overhead, improved transient performance, and robustness against parametric fluctuations [42].

Gomez et al. presented a novel method for estimating a microgrid's primary frequency response (PFR). Combining the finite control set-model predictive control (FCS-MPC) with droop control enables wind turbines to operate resiliently. The proposed controller improves frequency regulation when applied to the grid-side converter (GSC) of a doubly fed induction generator (DFIG) under windy conditions [43]. Chen et al. developed a two-step FCS-MPC technique for islanded AC microgrids with an enhanced transient response, flexible scalability, low hardware price, and good stability [44].

Aboelsaud et al. used FCS MPC to control a standalone inverter in standard modes and ride through faults without degradation. It controls the fault current with minimum distortion and provides high-quality voltage regulation [45]. Poonahela et al. developed a finite control state model predictive control with several distributed energy resources in microgrids that can track the load and reference power, thereby enabling power balancing [46]. Azab et al. presented the FCS-MPC approach for managing the active and reactive powers of MGs. They offered a low-voltage ride-through (LVRT) capacity for the inverter during voltage dips [47]. The findings are summarized in Table 1

B. CONTINUOUS CONTROL SET MODEL PREDICTIVE CONTROL (FCS-MPC) OF MICROGRIDS

The continuous control set model predictive control (CCS-MPC) technique employs modulated continuous-time signals. Unless a combinatorial explosion occurs, larger prediction horizons can be used. This method produces an average spectrum with zero tracking error. A block diagram of the CCS MPC recreated from [47] is shown in Figure 7, where the modulator and power converter are connected directly. The modulator performs pulse-width modulation based on the duty-cycle signal d(t). The desired reference signal w(t+1) and plant signals x(t+1) and y(t+1) are used to calculate the switching operations. The duty cycle signal d(t) is determined using the cost function j.

Generalized predictive control (GPC) and explicit MPC are two distinct CCS-MPC variants. The first approach calculates the optimal input value by solving the optimization problem in real time, whereas the second method uses a lookup table. The complexity of the GPC is independent of the prediction

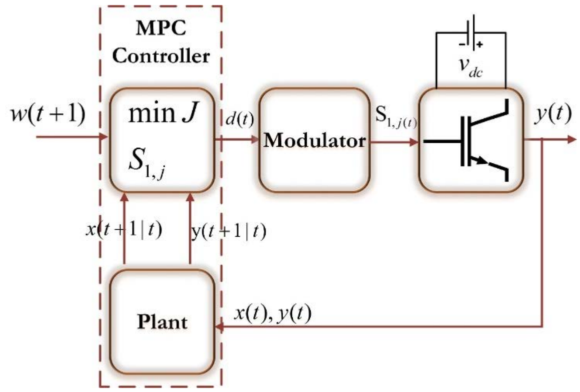

FIGURE 7. A Block diagram of CCS MPC.

horizon. GPC controllers create the required historical states and predictions for the GPC algorithm using a controlled autoregressive moving average (CARIMA) model.

Zhou et al. stabilized the constant power needs in DC microgrid systems with the help of an adaptive continuous control set model predictive control. Although the recommended method provides improved dynamic performance, it exerts a larger computational burden on the CPU [48]. To ensure the stability and resilience of buck power converters in DC microgrids, Zhou et al. devised a unique continuous control model for predictive control. This approach works adequately in terms of load and input voltage fluctuations, settling time, and overshoot [49].

Ceron et al. suggested a generalized predictive controller for wind turbines that offers microgrid frequency support. These outcomes enhance the frequency responsiveness of the microgrid, decrease oscillations, and increase the frequency nadir [50]. Li et al. developed a decentralized composite generalized predictive control (DCGPC) technique for DC microgrids with high PV integration. Compared to a typical double-loop PI controller, the DCGPC has significantly improved transient-time control performance and a larger stability margin. It enhances the power quality, robustness, and reliability [51]. Toso et al. worked on the predictive current regulation of a microgrid-connected PWM inverter using a continuous control set model. Under critical circumstances, such as fault occurrences, the local behavior of the grid improves, while the scalability and compatibility of the controllers are enhanced [52]. Owing to its fixed-frequency operation, CCS exhibits superior performance over FCS. However, the computational length of this method poses a significant challenge. A suitable computation algorithm has a short computational length which has short memory requirements and easy management. The findings are summarized in Table 2. The contributions and limitations of each configuration explained.

V. MICROGRIDS SECONDARY CONTROL: MPC-BASED POWER SHARING

The two main functions of microgrid secondary control layer are controlling the voltage and frequency deviations introduced by primary control layer. Figure 8 recreated

TABLE 1. Application of FCS MPC for power quality enhancement.

Configuration	Contributions	Validation	Limitations	Ref
Islanded System with RES, Electric Storage, and utility grid	Average Switching Frequency (ASF) and Voltage Total Harmonic Distortion are decreased (THD)	Laboratory Test Bench	Multiple parallel coupled DG units increase the computational complexity	[41]
Islanded System with PV, wind turbine, and utility grid	Excellent steady-state performance, reduced computational overhead, enhanced transient performance, and resistance to parametric perturbations.	Simulation	Controller Stability is not guaranteed	[42]
Wind Turbine, Electric Storage, and utility grid	Improved Frequency Regulation	Simulation	Reactive Power Balance not included	[43]
Islanded System with DG's	Improved steady-state and transient response	Laboratory Test Bench	Steady State Error not considered	[44]
Standalone Microgrid Inverter	Better voltage regulation and ride through fault without deterioration	Laboratory Test Bench	Power Sharing Issue under fault condition for multi-inverter	[45]
Islanded and interconnected system with DG's	Better Power Sharing achieved	Simulation	Track varying power generation and dynamic load change, allowing easy power-sharing	[46]
Grid Connected System with PV and Energy Storage	Low Voltage Ride Through (LVRT) during voltage Sag improve dynamic performance and flexible control	Simulation	Limited configuration as only PV System considered	[47]

TABLE 2. Application of CCS MPC for power quality enhancement.

Configuration	Contributions	Validation	Limitations	Ref
Islanded System with PVs, Electric Storage, and utility grid	The adaptive CCS-MPC approach mitigates the system instabilities and provides superior dynamic performance compared to the conventional CCS-MPC approach	Simulation and Laboratory Test Bench	Increased Computational requirements and high burden on the CPU	[48]
Islanded System with PV, wind turbine, and utility grid	Steady-state error due to system disturbances is reduced. Recovery, settling time, and overshoot exhibit improved	Simulation and Laboratory Test Bench	Increased computational requirements and Limited configuration as only PVs considered	[49]
Wind Turbine, Electric Storage, and utility grid	Generalized Predictive Control enhances the frequency responsiveness of the system, decreases frequency deviations, and raises the frequency nadir value.	Simulation	Reactive Power Balance not included	[50]
Autonomous System with high PVs penetration, Electric Storage, and electric vehicle	The power quality and system dependability enhanced transient-time control performance and a wider stability margin.	Simulation	Research work is limited to the idealized system and should be extended to the whole system	[51]
Microgrid connected PWM inverter with energy storage	Enhances the flexibility and adaptability of the controllers. Improves the local behavior of the grid under critical scenarios, such as fault occurrences.	Laboratory Test Bench	The scope of the investigation is restricted to a few anomalous bus voltage and frequency circumstances.	[52]

from [53] shows these control features of microgrid secondary control layer. Microgrids can integrate different types of storage technologies, including batteries, ultracapacitors, pumped hydroelectric storage (PHS), flywheels, compressed air energy storage (CAES), superconducting magnetic energy storage (SMES), and hydrogen storage systems. A hybrid energy storage system (HESS) improves performance by lowering operating costs, enhancing power rating, increasing lifetime, and reducing degradation. Microgrids frequently employ lithium-ion batteries in modular systems, which incurs lower maintenance costs. They have a limited number of life cycles, poor degradation, current ripple generation, and toxicity [54], [55].

A battery management system (BMS) is employed for cell protection, balancing, charge/discharge control, and state of health (SOH) estimation. The MPC cost function considers battery degradation to optimize the economic concerns of the system [56], [57]. Another energy storage system,

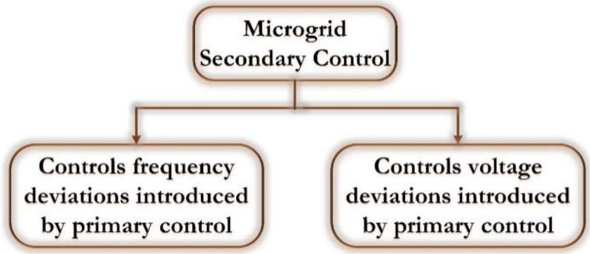

FIGURE 8. Microgrid secondary control layer.

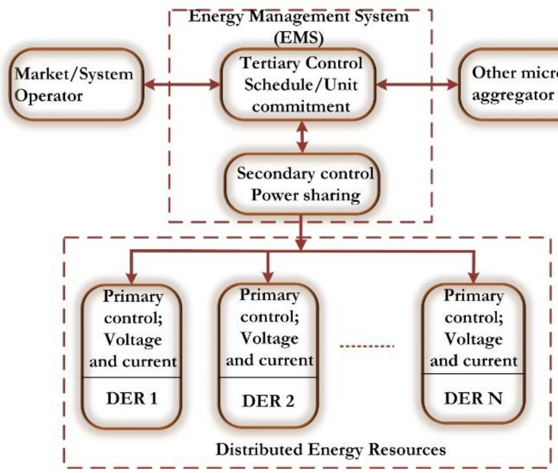

FIGURE 9. Power sharing at the secondary control layer.

an ultracapacitor or supercapacitor, delivers charges faster than batteries. They have a higher tolerance for charge cycles than batteries [58]. Hydrogen storage systems exist in two forms: compressed hydrogen and metal hydride. However, this technology has a high specific energy and low toxicity. Its cycle efficiency is low, and its life cycle is limited to a few hours [59], [60].

The flywheel storage system has an intermediate position between ultracapacitors and batteries in terms of power and energy levels. It exhibits quick charge/discharge features, temperature-resistant behavior, and a longer lifetime [61]. SMES is favored for better power quality applications because of its high specific power, low specific energy, quick response, and extended lifespan. A CAES offers large-scale storage capacities owing to its lower start-up time and longer life cycles [62]. The PHS is a traditional, low-cost, and environmentally friendly energy storage method for electrical grids. It provides high-efficiency energy conversion without harmful emissions. However, the requirement for larger land spaces limits its scope in modern microgrids [63], [64].

A. MICROGRIDS ENERGY MANAGEMENT SYSTEM

Sustained electric power delivery to local loads is possible using an appropriate energy balancing method. It is developed by an energy management system (EMS), that minimizes operational costs and enhances system efficiency. The excess energy from renewables in the microgrid is delivered to the ESS, and the energy deficit is supplied by storage units [65]. The MPC-optimized EMS manages the energy generation, consumption, and exchange following the load. The optimization process is integrated into the feedback loop. The necessary control actions are computed by analyzing the disturbances and new grid states [66]. Standard MPC procedures include linear programming (LP), quadratic programming (QP), nonlinear programming (NLP), mixed integer linear programming (MILP), mixed integer quadratic programming (MIQP), and metaheuristics. The choice of a particular procedure depends on the cost function and model [67], [68]. After calculating the optimal set points for the MG, the predictive controller transmits the control signals to the converter module. These set points are determined using the mode of operation, charge profile of the ESS, operation of the DER modules, state of unit commitment, and economic dispatch.

Figure 9 recreated from [69] shows the interaction between the secondary control layer and other layers in a microgrid. The tertiary control layer performs the unit scheduling and commitment. Calculations are performed based on data from neighboring microgrids and market system operators. The secondary control layer uses computational data from the tertiary layer and controls the primary control layers.

The MPC-EMS of Microgrid has the following aims

- Ensure efficient power flow between different units to maintain the energy balance
- Ensure the flexible operation maintains specific weights in the cost function
- Lowering the energy exchange in the grid-connected mode and higher levels of renewable energy are available.
- Protection of Battery Energy Storage System (BESS) from overcharging and deep discharging
- Enhancing the energy efficiency of power plants that operate the most efficient units.

Figure 10 recreated from [69] shows a block diagram of the energy management system for the microgrid. An energy management system controls power exchange among renewables, storage devices, and controllable loads. The EMS considers the generation forecasting, demand prediction, and electricity market prices for proper power sharing. Information regarding the exchange of active/reactive power between the transmission and distribution system operators is necessary for energy management in a microgrid. An appropriate load current is supplied according to the power exchanged with the external grid. Grid reliability is maintained by proper coordination among the electric storage units. A battery energy storage system (BESS) is optimized to efficiently utilize available resources.

Morato et al. focused on the fault-tolerant energy management problem of renewable energy microgrids. They introduced a model predictive controller (MPC) synthesized using a linear parameter-varying (LPV) prediction model. The MPC is tuned to enhance the share of renewable energy resources with maximum efficiency de [70]. Nair et al. developed a novel control strategy for a microgrid with high PV penetration, dispatchable generators, and hybrid

TABLE 3. A review of various MPC energy management strategies in microgrids.

Objective	Method	Contributions	Limitations	Ref
To develop a fault-tolerant Energy Management System for microgrids	A modular Fault Tolerant Control arrangement based on a bank of observers Fault Estimation system and Model Predictive Control	FTC approach readjusts MPC Prediction Model online concerning estimation of faults providing superior performance to simple MPC	The robustness requirements of the suggested Fault Tolerant Control technique are not tested yet	[70]
To improve the operating efficiency of the microgrid, enhance the energy utilization of renewable and lower the battery system degradation	The energy scheduling system based on MPC	Significant decrease in battery dwell time at high SOC levels, smoother setpoint fluctuation in the regenerative fuel cell, and reductions of about 50 percent and 80 percent in PV power curtailment and dispatched generator use with MPC.	The performance of MPC is not accessed when there is uncertainty in the forecast	[71]
To provide robustness in Microgrid Clusters against system uncertainties induced by renewables and load demand	Based on tube-based model predictive control, a unique energy management paradigm for off-grid microgrid clusters.	The proposed method can withstand external disturbances in the energy scheduling technique. There is a low compromise on computational efficiency and performance.	The stability of the controller is not guaranteed	[72]
To undertake power management in a standalone DC microgrid to ensure the system's reliability and stability.	The Autoregressive Integrated Moving Average (ARIMA) algorithm is included in a novel power management technique to anticipate the load and environmental factors.	It has improved power management between generators, storage devices, and loads.	Distributed MPC-based power Management is disregarded.	[73]
To reduce daily household energy expenses, optimize solar self-consumption, and eliminate energy waste for a residential Microgrid System.	A hierarchical two-layer home energy management system is developed. The upper layer consists of an MPC optimized with Mixed Integer Linear Programming, and the lower layer consists of a rule-based real-time controller.	For the same battery capacity, a Two-layer system offers superior PV consumption, more energy savings, a decrease in home operation costs, and adequate compensation for energy forecasting errors.	The scope is limited to home Microgrid System	[74]
To implement Probabilistic Microgrid Energy Management with Interval Predictions capability in autonomous Microgrids.	A hybrid technique integrating scenario-selected optimization and reserve strategy is created using the model predictive control.	A good balance between the microgrid's resilience and efficiency was achieved. The suggested strategy gives excellent economic performance and does not require significant predictive accuracy.	Limited to isolated Microgrids	[75]
Building an EMS for microgrids with a hybrid energy storage system to ensure good self-consumption scores at the lowest possible cost	A Hierarchical Model Predictive Controller (HMPC) with two levels is created. It consists of two data-driven algorithms: a Real-Time Model Identification (RTMI) module and an MG cost estimator.	The hierarchical controller evaluates the yearly rate of self-consumption and microgrid operation to decide which energy storage device must operate daily. A compromise was reached between the microgrid's price, profit, and energy independence.	The controller has a limited robustness	[76]

energy storage capacity. Based on the MPC, they built an energy-scheduling system for low-cost and sustainable operations. The MPC is vital for moving the battery charging to the peak generation period. It allows a smoother setpoint variation of the fuel cells and maximizes PV power usage [71]. Xie et al. performed reliable online energy scheduling in microgrid clusters to achieve robustness against system uncertainties. They perform multistage optimization using a coordination algorithm known as the compound alternating direction method of multipliers (C-ADMM) [72]. Batiyah et al. designed a power management system (PMS) for an autonomous DC microgrid. They combined the model

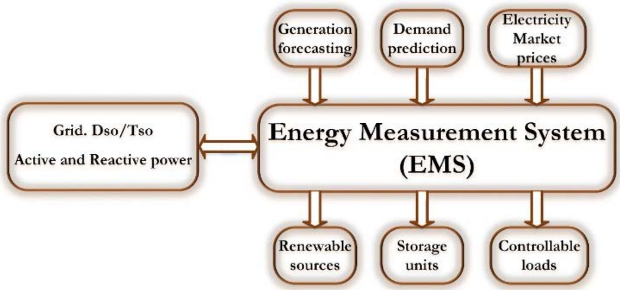

FIGURE 10. Block diagram of the energy management system.

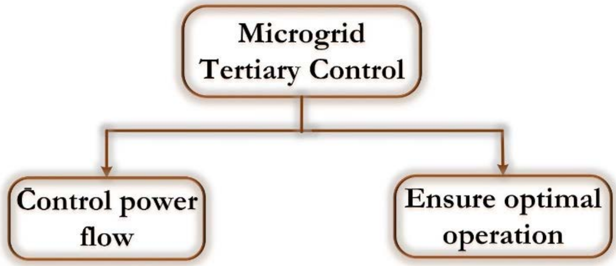

FIGURE 11. Microgrid tertiary control layer.

predictive control (MPC) approach and autoregressive integrated moving average (ARIMA) forecasting techniques. The proposed strategy regulates the DC bus voltage at a set point. The PV and wind turbines operate at the maximum power point [73]. Elkazaz et al. introduced a multilayer home energy management system to minimize daily household energy expenses and maximize solar self-consumption. The upper layer has a model predictive controller that optimizes household energy consumption using mixed-integer linear programming. The bottom layer contains a rule-based real-time controller that calculates the appropriate power settings for the home battery storage system. Multilayer residential energy management systems can reduce utility costs and increase solar energy self-consumption [74]. Cheng et al. utilized a technique that uses information supplied by time intervals to increase economic performance. The reliability and stability are maintained using a reserve strategy. A good compromise between reliability and efficiency of the microgrid is achieved [75]. Yamashita et al. proposed a two-layer model predictive controller with two data-driven modules. There are two data-driven algorithms: a real-time model identification (RTMI) module and an MG cost estimator [76]. These contributions of each technique and its limitations are summarized in Table 3

VI. MICROGRIDS TERTIARY CONTROL: MPC-BASED ECONOMIC OPTIMIZATION

The two main function of microgrid tertiary control layer are to control power flow and ensure optimal operation. Figure 11 recreated from [77] shows these control features of microgrid tertiary control layer A hybrid energy storage system (ESS) is optimized to improve power sharing, reduce energy costs, and enhance system reliability. The model predictive controller protects the ESS from abnormal load transients, manages the battery charging state, regulates the DC voltage and current drawn from the battery system.

MPC combines ESS models into a microgrid to restrict the number of charge cycles. This strategy prevents battery deterioration, determines the cost of energy exchange with the central grid system, and rationalizes the power price [78]. Tertiary microgrid control regulates the active/reactive power exchange with the external grid and optimizes the microgrid economically [79]. The MPC tertiary controller analyzes the demand forecast and operational cost data. It develops an ESS dispatch schedule and feeds the output signal to a secondary controller [80]. The secondary control is based on real-time measurements of the active and reactive powers. Energy forecasts are used at the tertiary control level for economic optimization [81]. The day-ahead market MPC strategy proposes demand bids and generation offers for the day before market closure. Participants are bound not to deviate from their contracts [82]. This strategy is better for small production and consumption prediction horizons. Advanced electrical markets employ intraday MPC flexible scheduling. The system operator is responsible for managing real-time energy balances. As the power system becomes congested, the system operator uses an MPC ancillary service. It helps regulate electric power quality, manage real-time constraints, and avoid power deviations [84]. Figure 12 recreated from [83] shows the cascade interconnection of tertiary MPC controllers in a microgrid. It performs computations using energy forecasts and price reductions. The plant model is connected to a feedback loop to adjust for external disturbances. The results of the tertiary-level calculations were submitted to an energy management system. Thus, market data are used to control the amount of energy exchanged between energy storage devices and the external grid.

A. DEMAND SIDE MANAGEMENT AND MPC FORMULATION

Demand-side management (DSM) helps lower the energy consumption and manages the load profile. It performs efficient electricity utilization on the consumer side without installing new infrastructure [85], [86]. In Demand Response (DR), consumers adjust their loads to obtain low-priced electricity and avoid peaks in the load profile [87]. There are deferrable loads, such as electric vehicles, vacuum cleaners, and iron, where the operating time slot can be shifted. However, for certain adjustable loads, the consumption can be moved to lower levels, such as in air conditioners and heating systems. Achour et al. developed a demand response strategy to reduce peak demand on an intelligent campus. Including model predictive control optimizes the power interchange between various microgrid components. Peak shaving avoids abrupt peaks in the load profile and maintains steady power flow [88]. Mehmood et al. established an efficient distributed MPC technique for isolated microgrids. This demonstrates the enhanced economic dispatch and intermittent control of the DRES. This approach enables rapid convergence

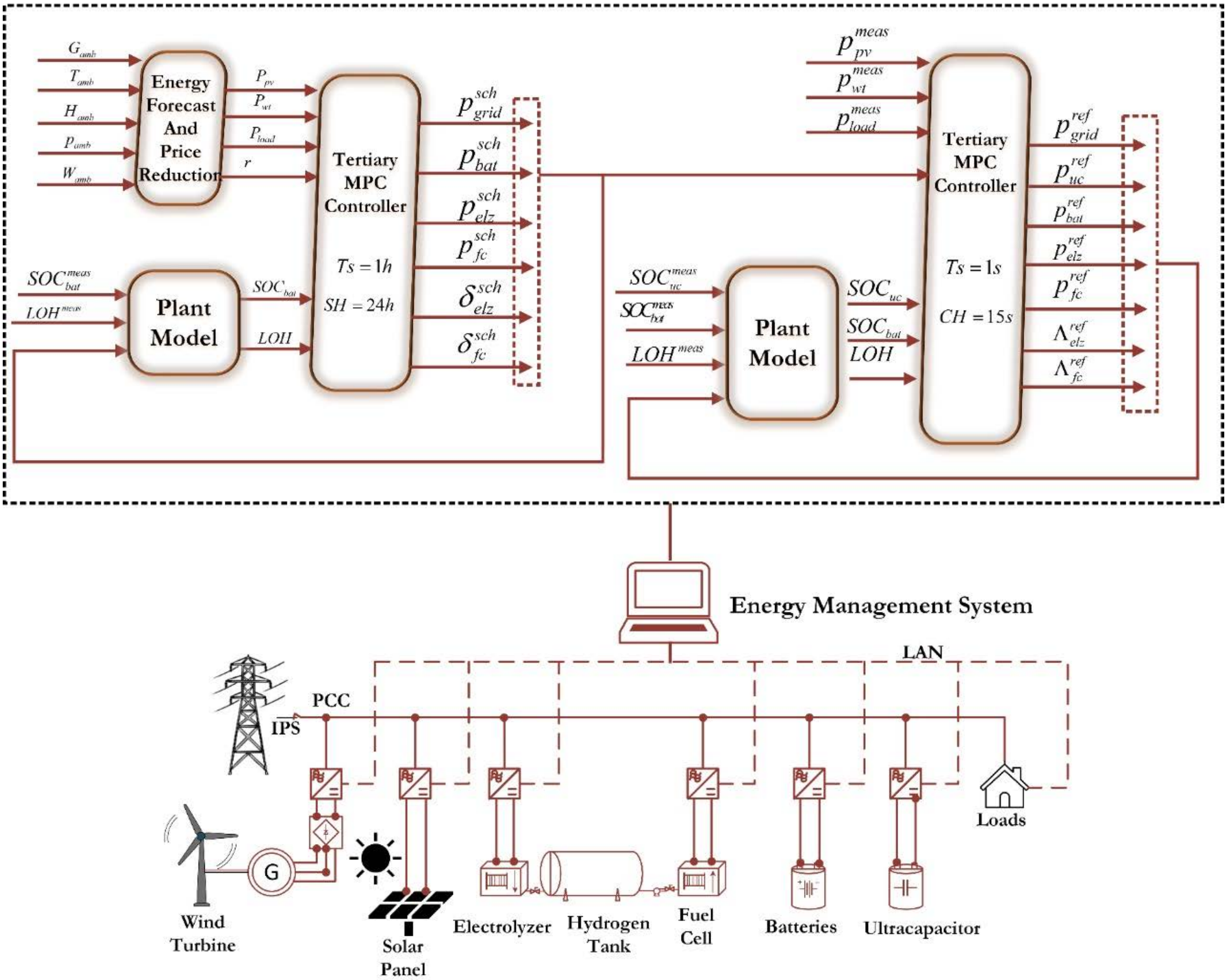

FIGURE 12. Cascade interconnection of tertiary controllers operating with an energy management system in a microgrid.

and manages the unpredictability of DRES [89]. He et al. exploited MPC to create and schedule energy market-trading strategies. They examined the forecast inaccuracies and uncertainties to develop a viable and cost-effective technique. The intraday multi-time scheduling approach is more precise, cost-effective, and practical than others [90]. Thanh et al. combined MPC with a voltage-dependent demand response and optimal battery dispatch. This strategy increases system reliability, prevents load shedding, and reduces battery deterioration [91]. Ndwali et al. focused on the demand-side management of a microgrid using PVs and a diesel generator as a backup energy system. This increases the system's resilience and reduces operating expenses [92]. The load frequency control strategies are used to tackle intermittent behavior of renewables [93]. The findings are summarized in Table 4

VII. FUTURE SCOPE OF WORK

Our reliance on fossil fuels for electricity generation has decreased as renewable energy alternatives are quickly adopted. The concept of a microgrid has become increasingly popular. Power quality, sharing, and economic control concerns arise from the high-level integration of RERS in microgrid architectures. Although numerous cutting-edge control strategies have been developed to enhance microgrid architectures, more can always be implemented. The MPC technique presents a problem in managing the prediction horizon length because a longer one might increase the computational complexity while increasing the efficiency. In the presence of system faults, tuning the MPC for the highest percentage of renewable energy sources and improving system efficiency is difficult. MPC can be used to protect batteries in hybrid energy storage systems (HESS); however, it is challenging to manage the power exchange with the primary grid. Future MPC development analyses should focus on the following research areas, using a variety of methodologies.

- Managing the computational complexity of extended prediction horizons while maintaining power quality, enhancing reliability, optimizing power sharing,

TABLE 4. A review of various MPC demand side management strategies in microgrids.

Method	Validation	Contribution	Limitation	Ref
MPC-based Demand Response Scheme	Simulation	Reduce the campus' peak demand while maintaining the state of charge of Energy Storage System (ESS), Electrical Vehicles (EVs), and Electrical Bikes (EBs)	There is a trade-off between storage losses and local balancing	[88]
Secondary Distributed MPC	Simulation	Rapid convergence and prediction of future planned modifications for economic dispatch	Voltage control and reactive power distribution are absent.	[89]
MPC-based robust energy market scheduling	Simulation	Manages low-frequency prediction error and uncertainty components. Reduce the differences between the day-ahead scheduling plan and the actual economic scheduling outcomes when there are errors and uncertainties in source and load forecast.	Economic optimal dispatching of power not discussed	[90]
MPC-based integrated voltage-based demand response	Simulation	Improves the operating cost by around 41.95% while enhancing the resilience with the slightest voltage deviation	Higher computation costs need to address the real-time problems with economical solutions.	[91]
Economic MPC	Simulation	Minimizes the Grid fuel cost, enhances the grid efficiency, robustly deals with disturbances and uncertainties	The practical implementation is not proven	[92]

and implementing low-voltage ride-through in a Microgrid.

- Enhancement of controller stability, performing the reactive power balance, and lowering the steady state error while enhancing the high penetration of RERs
- Development of a Robust Fault Tolerant Energy Management System with an adjustable prediction model for better operation under fault conditions
- Development of Multilayer and Multi stage hierarchal control strategies and optimization with some of the efficient methods like linear programming to reduce operation cost and compensation of uncertainty in energy forecasting
- Development of MPC-based optimized Demand Response Strategies for improving the operating cost, enhancing robustness, handling power system uncertainties, and economical scheduling

VIII. CONCLUSION

MPC is a sophisticated control approach used in microgrids to provide efficient, reliable, flexible, and optimal power delivery. It is used in the three control layers of the microgrid. The main objective of MPC-based control systems is to use a feedback mechanism to handle the system disruptions due to intermittent nature of RERs, demand changes, and load disconnections. This article presents various MPC-based control systems that have been enhanced using various optimization algorithms for Microgrids with high RER penetration. The benefits and drawbacks of recent improvements in MPC structures were briefly discussed. The conclusion of this study emphasizes the importance of expanding the development of MPC architectures for microgrids energy management, power sharing and optimization. This study is anticipated to offer useful data for investigation of MPC techniques at various microgrid layers.

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