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Global Optimal Automatic Generation Control of a Multimachine Power System Using Hybrid NLMPC and Data-Driven Methods

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Abstract: Real-world power systems face challenges from demand fluctuations, system constraints, communication delays, and unmeasurable disturbances. This paper presents a real-time hybrid approach integrating Nonlinear Model Predictive Control (NLMPC) and data-driven methods for automatic generation control (AGC) of synchronous generators, particularly under cyber-physical attacks. Unlike previous studies, this work considers both technical and economic aspects of power system management. A key innovation is the incorporation of a detailed thermo-mechanical model of turbine and governor dynamics, enabling optimized control and effective management of power oscillations. The proposed NLMPC-based AGC strategy addresses governor saturation and generation rate constraints, ensuring stability. Extensive simulations in MATLAB/Simulink, including IEEE 11-bus and 9-bus test systems, validate the controller's effectiveness in enhancing power system performance under various challenging conditions.

Keywords: automatic generation control; nonlinear model predictive control; data-driven model; synchronous generators

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1. Introduction

1.1. Importance

Due to their inherently unpredictable and variable nature, renewable energy sources (RESs) present significant challenges to system stability and economic efficiency as a result of increasingly being integrated into electrical grids, [1–3]. The fluctuating and uncertain outputs of RESs lead to non-zero mean demand disturbances, which can undermine the effectiveness of economic dispatch (ED) and automatic generation control (AGC) in power systems. Traditional approaches to optimizing operational costs under these stochastic conditions often fall short because they primarily focus on steady-state solutions, neglecting the complexities of dynamic system behavior, such as governor saturation and generation rate constraints (GRCs) [4]. Synchronous generators, particularly those driven by thermal power plants, are vital for maintaining the stability and reliability of the electrical grid. The automatic generation control of these thermal generators is highly intricate and nonlinear, with system components continually adapting to changing operational conditions [5]. AGC is utilized to regulate the power output of various generators located at different power plants, in response to changes in the load. To ensure the reliability of power systems, especially during unforeseen disturbances like cyber-physical attacks, robust control mechanisms capable of independently regulating both the generator's output

voltage and power are essential [6]. In this context, dynamic model predictive control (MPC) has emerged as a promising approach for optimal generation control, offering the flexibility to incorporate a wide range of constraints and enabling real-time adjustments [7].

However, existing MPC-based AGC strategies have primarily focused on optimizing control performance without fully addressing the simultaneous achievement of technical and economic objectives at the system level. This gap underscores the need for a novel approach that integrates both technical and economic considerations into a cohesive control strategy [8]. The research presented in this paper addresses this critical need by proposing a distributed nonlinear model predictive control (NLMPC) framework with state constraints [9]. This advanced approach not only optimizes control performance but also ensures economic efficiency at the system level, representing a significant advancement in the field. As the global integration of RESs into power grids accelerates, the challenges posed by these variable energy sources demand innovative control strategies that can adapt to real-time operational conditions and the dynamic nature of power systems. The proposed methodology offers a comprehensive solution that enhances the stability, reliability, and economic efficiency of power grids, positioning AGC systems to remain resilient and cost-effective even as dependence on renewable energy sources grows. Ultimately, this research contributes to the broader objective of transitioning to a more sustainable and resilient energy infrastructure, addressing the complex interplay between technical and economic challenges in the integration of renewable energy into the power grid. In the following section, a comprehensive literature review is conducted to assess the recent state-of-the-art research in this area. This review aims to provide clarity on the current advancements and identify gaps that the proposed methodology seeks to address. By examining the latest studies and developments, it will be better understood how recent approaches have tackled the challenges associated with the integration of renewable energy sources into power grids and the optimization of control strategies under stochastic conditions.

1.2. Literature Review

The application of MPC for AGC in power systems has been thoroughly investigated, with various methodologies exhibiting different levels of success in addressing the complexities of modern power grids. These MPC-based techniques differ significantly in their control architectures, objectives, and the specific dynamic challenges they aim to address.

1.2.1. Centralized vs. Distributed MPC Approaches

MPC strategies, whether centralized or distributed, commonly focus on regulating the ACE, which manages both tie-line power flows and frequency deviations to uphold system stability. In centralized configurations, as discussed in [10], MPC functions in a supervisory capacity, setting optimal targets for local proportional–integral (PI) controllers. This supervisory role ensures that even during communication failures, local controllers can independently maintain ACE, providing a resilient control framework, as evidenced in studies like [11,12]. This approach proves effective in scenarios where centralized control might be compromised by communication issues. However, centralized MPC implementation is often constrained by its high computational and communication demands, particularly in large-scale power systems [13]. To overcome these limitations, distributed model predictive control (DMPC) has been proposed, as detailed in works like [10,14–16]. DMPC strategies decentralize the control process across multiple controllers, reducing the computational load and enhancing the scalability of the system. An in-depth review of various distributed MPC implementations for AGC can be found in [17]. A significant development within DMPC is the hierarchical MPC scheme introduced in [18],

which extends control capabilities to include novel resources in smart grids. Despite this advancement, this approach overlooks the critical role of conventional turbine-governors in frequency regulation, highlighting the need for more comprehensive control strategies that incorporate both traditional and modern resources.

1.2.2. Limitations of ACE-Based MPC Schemes

Despite advancements, ACE-based MPC strategies are not without their shortcomings. These approaches often converge to local optima, similar to traditional PI-based AGC, as their primary focus is on maintaining predefined tie-line flows and minimizing local control costs. This narrow focus can lead to biased control, particularly during significant disturbances, and fails to optimize the system-wide economic dispatch (ED), as noted in [19]. Additionally, ACE-based MPC schemes lose their capacity to smooth wind fluctuations, a crucial function in grids with high levels of renewable energy integration. To address these issues, a state-constrained DMPC (SCDMPC) approach was proposed in [20], which introduces constraints on tie-line flows while simultaneously regulating frequency states. This method aims to achieve a cost-effective AGC by integrating ED and AGC objectives, allowing tie-line flows to adapt during the AGC cycle. However, this approach is based on the assumption of instantaneous communication between distributed controllers and the wide area control (WAC) system, and minimal demand disturbances—conditions that are often impractical in real-world applications. In large-scale power systems, communication delays are inevitable, and significant demand disturbances can activate input constraints, potentially leading to the infeasibility of the SCDMPC optimizer.

1.2.3. Nonlinear Dynamics and Advanced Control Strategies

The complexity of AGC is further compounded by the nonlinear dynamics of synchronous generators, especially in systems powered by thermal plants. Research conducted in [21] focused on the speed regulation of turbo generator systems, emphasizing the critical role of the excitation system in optimizing performance and maintaining stability. The study highlights the challenges posed by managing the intricate dynamics of high-order models, such as the thirteenth-order steam turbine model discussed in [22,23]. Traditional control approaches, like linear optimal control theory, often fall short in these scenarios due to their sensitivity to operating condition changes and the frequent need to recalibrate controller gains. To mitigate these challenges, various studies have explored intelligent control techniques, such as fuzzy logic, neural networks, and hybrid control systems [24–26]. These methods offer the flexibility and robustness needed to handle nonlinear dynamics and varying operational conditions. Hybrid controllers, which combine traditional PID controllers with intelligent methods like neuro-fuzzy systems, have shown promise in managing the complex dynamics of turbo generators and other critical power system components [27].

1.2.4. Integration of Renewable Energy Sources

The growing integration of RESs into power grids further complicates the control landscape. Despite the rapid expansion of renewable energy infrastructure, a significant portion of electricity generation continues to rely on conventional thermal power plants, particularly combined-cycle plants utilizing both steam and gas turbines [28,29]. Controlling these systems is especially challenging due to their nonlinear behavior and the difficulty of directly measuring critical parameters, such as magnetic flux in generators or internal pressure in turbines. Advanced control methodologies, including MPC, adaptive control, and fuzzy logic control, have been developed to optimize the performance of these complex systems. These strategies are designed to enhance efficiency, stability, and reliability by effectively managing load variations, disturbances, and changing operating

conditions [30–32]. However, the challenge of nonlinear optimal control remains a focal point of research, especially in simulated environments where the aim is to improve system performance through advanced control algorithms [33,34]. The body of research on MPC-based AGC strategies underscores the substantial progress made in creating robust and scalable control systems for contemporary power grids. Nonetheless, significant challenges persist, particularly in merging the economic objectives of ED with the technical demands of AGC, managing nonlinear system dynamics, and adapting to the rising integration of RESs. Continued research into more holistic and adaptive control strategies, such as state-constrained DMPC and intelligent control systems, is essential for enhancing the stability, reliability, and economic efficiency of future power systems [35–38].

1.3. Research Gaps

The literature on MPC-based AGC strategies has made notable strides in power system control, yet several critical shortcomings remain when compared to the proposed distributed NL MPC framework with state constraints. Table 1 provides a brief comparison of the shortcomings in previous research and how the proposed distributed NL MPC framework addresses these issues:

Table 1. Brief comparison of previous research and proposed framework.

Aspect	Previous Research	Proposed Distributed NL MPC Framework
Optimization Focus	Primarily local optimization (ACE-based), leading to local optima similar to traditional PI control [10–12,19].	Achieves system-wide optimization by integrating both control performance and economic objectives.
Handling Nonlinear Dynamics	Relies on linearized models, which are less effective in managing complex nonlinear dynamics [10–12].	Utilizes a nonlinear MPC framework that is better suited for the inherent nonlinear behavior of modern power systems.
Scalability and Flexibility	Centralized MPC faces scalability issues due to high computational/communication demands; DMPC lacks flexibility [24–26,33].	Offers a scalable and flexible control strategy that adapts to real-time operational conditions.
Integration of Economic and Technical Objectives	Often separates economic and technical goals, leading to suboptimal performance [33,34].	Integrates economic efficiency directly into the control framework, balancing both aspects effectively.
Response to Renewable Energy Variability	Struggles to manage the variability and unpredictability introduced by high RES penetration [10,14–16,18,20].	Designed to adapt to real-time challenges posed by RESs, enhancing grid stability and reliability.

1.4. Research Contribution

The contributions of this study can be listed as follows:

- The proposed hybrid NLMPC framework, integrated with data-driven methods, introduces a novel approach to AGC in multimachine power systems. This method offers significant advancements by effectively balancing technical and economic objectives, addressing real-world constraints, and providing robust, scalable, and adaptive control under dynamic conditions. The primary contribution of this paper lies in its comprehensive integration of technical and economic considerations into a unified control framework. Unlike prior studies that often prioritize either system stability or economic efficiency, the proposed approach incorporates a multi-objective cost function that simultaneously minimizes frequency deviations, voltage deviations, generation costs, and pollution penalties. This dual focus ensures that the system achieves optimal performance not only in terms of operational stability but also with respect to economic and environmental sustainability.

- A notable innovation of the present method is its advanced dynamic modeling, which integrates detailed thermo-mechanical dynamics of synchronous generators, including turbine and governor behaviors. In contrast to recent state-of-the-art methods that rely on simplified or linearized models, this approach combines physical modeling with data-driven techniques to improve the accuracy of system predictions and adapt to real-time operational changes. This integration enables the framework to address unmodeled dynamics and disturbances, such as cyber-physical attacks, load fluctuations, and renewable energy variability, which are significant limitations in existing methods.
- Another critical contribution of the paper is its approach to managing computational complexity, a known challenge for NLMPC methods. By leveraging data-driven techniques to approximate unmodeled dynamics, the framework reduces the computational burden associated with solving nonlinear equations. Furthermore, the hierarchical control structure distributes computational effort across primary, secondary, and tertiary levels, ensuring scalability and real-time feasibility for large-scale systems. Unlike many existing methods that face scalability issues or depend on unrealistic assumptions, such as ideal communication conditions, the proposed framework is designed to handle practical challenges, including communication delays and significant demand disturbances.
- The paper also stands out for its focus on sustainability, incorporating pollution costs, such as CO₂, SO₂, and NO_x, into the optimization framework. This alignment with global sustainability goals distinguishes the proposed method from many recent studies that overlook the environmental impact of power system operations. By addressing these concerns, the framework ensures that the AGC system not only meets technical and economic requirements but also supports environmentally conscious power generation. Compared to recent state-of-the-art research, the proposed method achieves system-wide optimization by integrating multiple objectives, effectively handling nonlinear system dynamics, and demonstrating exceptional adaptability to planned and unplanned disturbances, such as line outages and cyber-physical attacks. It consistently outperforms existing methods in terms of stability, cost-efficiency, and environmental impact. In conclusion, the hybrid NLMPC framework with data-driven integration represents a significant advancement in AGC for multi-machine power systems. Its ability to maintain system stability, minimize operational costs, and reduce environmental impact establishes it as a leading approach for modern power system management, addressing both contemporary challenges and future needs.

1.5. Organization

The current paper is structured into several key sections, each serving a distinct purpose. The paper was opened with an Introduction and overview, providing the context, objectives, and significance of the research. Section 2 delves into the conceptual model, offering a comprehensive discussion of the theoretical framework and foundational concepts that guide the study. Section 3 presents the mathematical formulation of the proposed method, detailing the equations, algorithms, and computational techniques employed. The proposed method is provided in detail in Section 4. Simulation results and discussions are presented in Section 5. Finally, Section 6 concludes the paper with a summary of the key conclusions, highlighting the main findings, contributions, and potential avenues for future research.

2. Conceptual Model for Coordinated Automatic Generation Control in a Multimachine Smart System

The conceptual model presented here outlines a comprehensive and integrated framework for a coordinated automatic generation control strategy within a multimachine smart system. This model is designed to simultaneously consider both the technical and economic aspects of the power system, ensuring a balanced and efficient operation that can effectively respond to physical contingencies.

2.1. Synchronous Generators in a Multimachine Smart System

At the core of this model are multiple synchronous generators, which operate within a sophisticated smart system infrastructure. These generators are connected within a network that demands high adaptability and efficient resource utilization to meet both technical and economic objectives.

2.2. Coordinated Automatic Generation Control Strategy

The proposed strategy emphasizes the coordination of both technical and economic goals:

- **Technical Objectives:** The model is designed to manage various technical parameters, including the control of power system oscillations (both local and inter-area), the management of voltage fluctuations, and the minimization of system losses. These technical aspects are critical for maintaining system stability and ensuring reliable power delivery.
- **Economic Objectives:** In parallel with technical management, the model seeks to optimize generation costs and ensure the efficient use of all available resources within the network. This economic optimization is crucial for reducing operational costs while maintaining high system performance.
- **Physical Contingencies:** The model includes strategies to address and mitigate physical disruptions within the system, ensuring that both economic and technical objectives are maintained even during unforeseen events.

2.3. Hierarchical Control System Based on Nonlinear Model Predictive Control (NLMPC)

The control strategy is structured into a hierarchical system, with different levels of control tailored to specific aspects of the power system:

- **Primary Level:** This level focuses on the real-time monitoring and control of power flow and generation costs. It ensures that the system operates within optimal parameters at all times.
- **Secondary Level:** This level manages the technical aspects of the system, such as oscillations, losses, and voltage fluctuations. It ensures that the system remains stable and efficient from a technical standpoint.
- **Tertiary Level:** This level involves the continuous adaptation and optimization of system resources. It dynamically adjusts generation and load balancing strategies to maintain overall system efficiency and effectiveness.

2.4. Integrated Model for Real-Time Adaptability

The conceptual model is designed to be highly adaptable, with continuous monitoring and control mechanisms that enable real-time data acquisition and feedback loops. This adaptability is crucial for optimizing system performance continuously, ensuring that resources are allocated efficiently based on real-time data, and adjusting strategies as needed to respond to changing conditions.

2.5. Economic and Technical Considerations

A key feature of this model is its ability to balance economic and technical objectives simultaneously. The model coordinates these objectives to ensure that the power system operates optimally, with neither economic efficiency nor technical performance being compromised. This conceptual model, which is shown in Figure 1, represents a holistic approach to power system management, integrating both economic and technical considerations into a single, adaptable framework that can respond to the dynamic demands of a multimachine smart system.

According to the conceptual model which is shown in Figure 1, the proposed framework for AGC integrates NLMPC with data-driven methods to address dynamic challenges in multimachine power systems. The process begins with system monitoring and data acquisition, where real-time measurements of critical variables such as voltage, frequency, rotor speed, turbine temperature, and generator outputs are collected through sensors. Historical and real-time data are logged to support further analysis, and disturbances, including sudden frequency or voltage deviations and line outages, are promptly identified. The next stage involves dynamic modeling and system identification. A dynamic state-space model is developed to capture the physical and electrical dynamics of the system, including equations governing rotor angle, speed deviations, turbine dynamics, and governor mechanisms. To enhance the model's accuracy, data-driven methods are employed to estimate unmodeled dynamics and disturbances. These methods predict nonlinear and time-varying behaviors that are not captured by first-principles models.

Using this integrated dynamic and data-driven model, the NLMPC framework enters the prediction phase, where it estimates the system's future behavior over a defined prediction horizon. A multi-objective cost function is formulated to optimize key objectives, including minimizing generation costs, frequency and voltage deviations, and emissions penalties. During this stage, the dynamic constraints of the system, such as governor saturation, generation rate constraints (GRC), and turbine thermal limits, are incorporated into the optimization problem. Real-time optimization follows, where the NLMPC solves the optimization problem to determine the optimal control actions that balance system stability requirements with cost minimization. The framework employs a hierarchical control structure consisting of three levels. At the primary level, real-time regulation of power flow and frequency is managed. The secondary level focuses on technical parameters such as oscillation damping, voltage regulation, and loss minimization. The tertiary level adapts generation schedules to balance technical and economic objectives over the long term. Control actions derived from the optimization are then implemented in real time. Optimized control signals, such as valve positions and excitation voltages, are sent to the respective components, including turbines and governors, for immediate execution. A feedback mechanism ensures continuous monitoring and adjustment of control actions in response to real-time system data, maintaining system stability and performance. A key innovation in the proposed framework is the error correction stage, where discrepancies between predicted and actual system behavior are identified. Data-driven models are periodically retrained using updated operational data to improve prediction accuracy. This adaptive capability allows the controller to dynamically respond to unmodeled disturbances and changes in system conditions, ensuring robust operation. The final stage focuses on performance evaluation and adaptation. Simulation results validate the effectiveness of the framework in minimizing deviations and optimizing operational costs under various scenarios. The system continuously updates its models and predictions, maintaining optimal performance during changing operational conditions or disturbances. By simultaneously considering economic and technical objectives, the proposed framework ensures a balance between minimizing generation costs and environmental penalties while maintaining operational reliability. It dynamically responds to demand and supply

changes, renewable energy source variability, and physical contingencies such as cyber-attacks or line outages. This staged process provides a robust, scalable, and adaptive control mechanism for multimachine smart systems, ensuring optimal performance across diverse operating conditions.

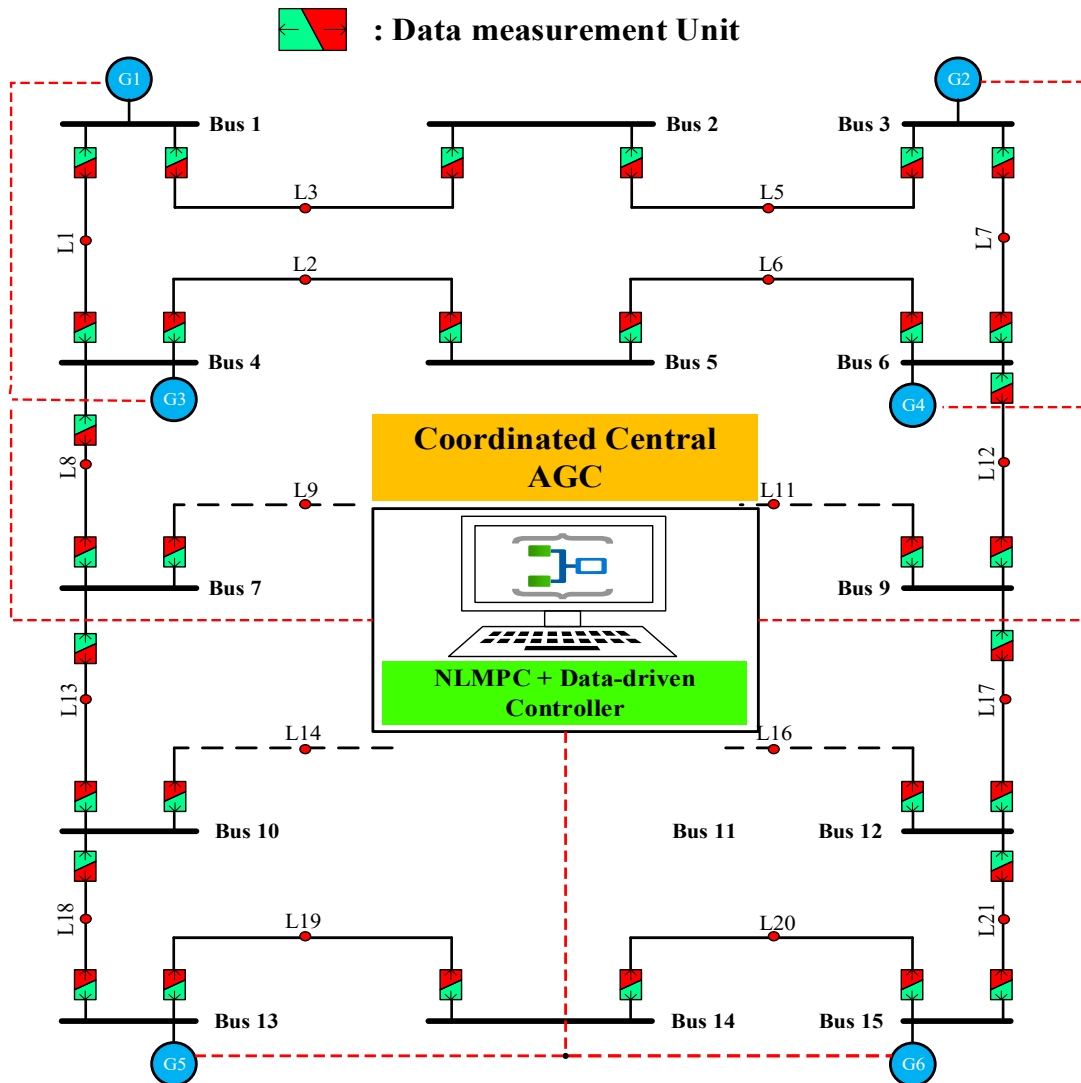


Figure 1. Proposed conceptual framework for an NLMPC-based approach to automatic generation control.

3. Dynamic Model of Synchronous Generator

A dynamic model of a synchronous generator is crucial for comprehending and analyzing the generator's behavior across different operating conditions, particularly regarding power system stability and control. In the following sections, a comprehensive dynamic state-space model of a synchronous generator, along with the dynamic models of the turbine and governor, is presented. This model encompasses the electrical dynamics of the synchronous generator, the mechanical dynamics of the rotor, and the control dynamics of the governor and turbine. The equations are provided in differential form, making them well-suited for implementation in nonlinear model predictive control (NLMPC) systems.

3.1. Electrical Dynamics

The rotor angle (δ) and rotor speed (ω) dynamics are given by [39]:

$$\frac{d\delta}{dt} = \omega - \omega_{ref} \quad (1)$$

where ω is the rotor speed and ω_{ref} is the synchronous speed.

The rotor speed (ω) dynamics are governed by the following differential equation:

$$\frac{d\omega}{dt} = \left(\frac{1}{2H}\right)(P_m - P_e - D(\omega - \omega_{ref})) \quad (2)$$

where H is the inertia constant, P_m is the mechanical power input from the turbine, P_e is the electrical power output, and D is the damping coefficient.

The electrical power output (P_e) is calculated using the following expression [39]:

$$P_e = \left(\frac{E'V}{X'_d}\right)\sin(\delta) \quad (3)$$

where E' is the internal voltage behind the transient reactance X' and V is the terminal voltage.

3.2. Field Voltage Dynamics

The internal voltage behind the transient reactance (E') is governed by the field voltage dynamics [39]:

$$\frac{dE'}{dt} = \frac{(E_f - E')}{T'} \quad (4)$$

where E_f is the excitation voltage and T' is the time constant of the field winding.

3.3. Governor Block

The governor controls the fuel supply to the gas turbine to regulate the mechanical power output P_m .

The speed error ($\Delta\omega$) is calculated as [39]:

$$\Delta\omega = \omega_{ref} - \omega \quad (5)$$

The governor adjusts the valve position (y_g) based on the speed error. The governor output is given by:

$$\frac{dy_g}{dt} = -\left(\frac{1}{T_g}\right)(y_g - y_{gref} + R\Delta\omega) \quad (6)$$

where y_g is the valve position, y_{gref} is the reference valve position, T_g is the governor time constant, and R is the droop coefficient. The valve position dynamics can be expressed as:

$$\frac{dy_g}{dt} = K_g\Delta\omega \quad (7)$$

where K_g is the gain of the governor.

3.4. Gas Turbine Block

3.4.1. Fuel System Dynamics

The fuel flow rate (F_f) dynamics are described by the following differential equation [39]:

$$\frac{dF_f}{dt} = \left(\frac{1}{T_f}\right)(y_g - F_f) \quad (8)$$

Where F_f is the fuel flow rate, and T_f is the time constant of the fuel system.

3.4.2. Compressor-Turbine Dynamics

The compressor-turbine power (P_{ct}) is calculated as [39]:

$$\frac{dP_{ct}}{dt} = \left(\frac{1}{T_{ct}}\right)(K_f F_f - P_{ct}) \quad (9)$$

where K_f is the turbine gain, T_{ct} is the time constant of the compressor-turbine, and P_{ct} is the mechanical power output of the turbine.

3.5. Mechanical Power Output

The mechanical power output (P_m) from the gas turbine is [39]:

$$P_m = P_{ct} - P_{loss} \quad (10)$$

where P_{loss} represents any mechanical losses in the turbine.

3.6. Overall System Dynamics

The overall state-space model of the system combines the dynamics of the synchronous generator, governor, and gas turbine. The state-space representation includes the following state variables:

δ : Rotor angle

ω : Rotor speed deviation

E' : Internal voltage

y_g : Valve position

F_f : Fuel flow rate

P_{ct} : Compressor-turbine power

The state vector (x) is defined as:

$$X = [\delta, \omega, E', y_g, F_f, P_{ct}]^T \quad (11)$$

The state-space equations can be written as:

$$\frac{dX}{dt} = AX + Bu \quad (12)$$

$$y = CX + Du$$

where:

$$u = [E_f, y_{g_{ref}}]^T \quad (13)$$

where matrix A represents the relationship between the current states and their derivatives. For this system, A would be:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -\frac{VE' \cos(\delta)}{2HX'_d} & -\frac{D}{2H} & \frac{V \sin(\delta)}{2HX'} & 0 & 0 & 0 \\ 0 & 1 & \frac{-1}{T'} & 0 & 0 & 0 \\ 0 & \frac{R}{T_g} & 0 & \frac{-1}{T_g} & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{T_f} & \frac{-1}{T_f} & 0 \\ 0 & 0 & 0 & \frac{K_f}{T_{ct}} & \frac{-1}{T_{ct}} & 0 \end{bmatrix} \quad (14)$$

Matrix B represents how the inputs affect the state derivatives. For this system, B would be:

$$B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \frac{1}{T'} & 0 \\ 0 & \frac{1}{T_g} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (15)$$

Matrix C maps the state variables to the output variables. For this system, assuming the outputs are δ, ω, P_e and P_m :

$$C = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ \frac{VE' \cos(\delta)}{X'_d} & 0 & \frac{V \sin(\delta)}{X'} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (16)$$

Matrix D represents the direct effect of the input on the output. For this system, typically, $D = 0$, meaning there is no direct feedthrough from the input to the output.

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (17)$$

4. Proposed Hybrid Model of NLMPC and Data-Driven Approach

The control system presented in this research is modeled using a combination of physical state-space equations and data-driven methods. The data-driven approach can be employed to model complex, nonlinear relationships that are difficult to capture with first-principal models alone or to identify model parameters in real-time.

In this study, a data-driven approach is incorporated into the NLMPC framework to enhance predictive accuracy and adaptability in AGC for multimachine power systems. The data-driven model is employed to approximate unmodeled system dynamics and disturbances, thereby improving the overall system response to uncertain operating conditions such as renewable energy fluctuations, cyber-physical attacks, and load variations.

The data-driven component compensates for the inherent limitations of purely physics-based models, which may not fully capture nonlinear behaviors, system uncertainties, and transient disturbances. By learning from real-time operational data, the data-driven model estimates the discrepancy between predicted and actual system behavior and integrates this correction into the NLMPC framework.

The proposed approach follows a structured implementation strategy to ensure accurate system predictions and effective control optimization. In the learning phase, real-time operational data, including generator states, control inputs, frequency deviations, and voltage fluctuations, are continuously collected. Machine learning techniques such as Artificial Neural Networks (ANNs), Gaussian Process Regression (GPR), and Long Short-Term Memory (LSTM) networks are employed to analyze system behavior and estimate unmodeled dynamics. The trained model is periodically updated using newly acquired data, allowing it to adapt to changing system conditions.

In the prediction phase, the trained data-driven model predicts unmodeled system dynamics and refines the physical model's predictions. These refined predictions are integrated into the NLMPC optimization process, which balances generation cost, voltage stability, and frequency regulation while ensuring operational constraints are met. The control phase involves applying the optimized control inputs derived from the NLMPC framework to the system in real time. The data-driven model continuously updates and refines its predictions to ensure robust performance in dynamic environments.

The integration of data-driven methods within the NLMPC framework provides several benefits. It improves accuracy by capturing complex system behaviors that traditional physics-based models may overlook. It enables adaptive learning by continuously updating using real-time data, ensuring responsiveness to evolving system conditions. Enhanced stability is achieved by improving the prediction of frequency and voltage deviations, thereby reducing control errors and system oscillations. Additionally, it optimizes generation costs while maintaining operational reliability and system security, ensuring economic efficiency.

This hybrid approach effectively balances technical and economic objectives, making it highly suitable for real-time AGC in modern power systems. Future work may explore additional machine learning techniques to further refine the adaptability and efficiency of the proposed method.

4.1. Physical Model

The state-space representation of each synchronous generator in a multi-machine system is:

$$\frac{dx_i}{dt} = f_i(x_i, u_i) + \epsilon_i(x_i, u_i, t) \quad (18)$$

$$y_i = g_i(x_i, u_i)$$

where X_i is the state vector of the i th generator, u_i is the control input vector for the i th generator, y_i is the output vector for the i th generator, and $\epsilon_i(x_i, u_i, t)$ represents the unmodeled dynamics or disturbances, which can be learned and corrected using a data-driven approach.

4.2. Data-Driven Correction

The error term $\epsilon_i(X_i, u_i, t)$ can be approximated using data-driven methods, such as machine learning models. The objective is to learn the mapping from states and inputs to the error term:

$$\epsilon_i(x_i, u_i, t) \approx \hat{\epsilon}_i(x_i, u_i) \quad (19)$$

This learned model $\hat{\epsilon}_i$ is then integrated into the NMPC framework to improve the accuracy of predictions.

4.3. Objective Function

The NMPC aims to optimize the operation of the power system by minimizing a multi-objective cost function that considers generation cost, voltage deviation, and frequency deviation, incorporating both the physical model and the data-driven correction.

$$J = \sum_{i=1}^{N_{gen}} \sum_{k=0}^{N-1} \left[\alpha_c C(u_i(k)) + \alpha_v (V_i(k) - V_{ref_i})^2 + \alpha_f (f_i(k) - f_{ref})^2 \right] \quad (20)$$

where the system dynamics include the data-driven correction:

$$x_i(k+1) = f_i(x_i(k), u_i(k)) + \hat{\varepsilon}_i(x_i(k), u_i(k)) \quad (21)$$

In this context, the following equation can be utilized to achieve the economic objective within the overall objective function, which focuses on minimizing the total generation cost of the system.

$$C(u_i(k)) = \sum_{i=1}^N C_{Gen,i,t}^{OP} + \sum_{i=1}^N C_{Gen,i,t}^{EMI} \quad (22)$$

In Equation (22),

$C_{Gen,i,t}^{OP}$ represents the generation cost of each power plant unit.

$C_{Gen,i,t}^{EMI}$ denotes the cost related to the pollution of the units in each time interval “t,” which can be defined as follows:

$$C_{Gen,i,t}^{OP} = \begin{cases} aP_{Gen}^2 + bP_{Gen} + c & \text{if } 0 < P_{Gen} < P_{Gen}^{rated} \\ 0 & \text{if } P_{Gen} = 0 \end{cases} \quad (23)$$

$$C_{Gen,i,t}^{EMI} = (C_{CO_2} \times CO_2 + C_{SO_2} \times SO_2 + C_{NO_x} \times NO_x) \times P_{Gen} \quad (24)$$

where the parameters in Equation (24) are defined as follows:

C_{CO_2} : Penalty factor for CO_2 production.

C_{SO_2} : Penalty factor for SO_2 production.

C_{NO_x} : Penalty factor for NO_x production

4.4. Constraints

The NMPC must respect several constraints, ensuring that the control actions are feasible and safe:

- State Constraints:

This includes limits on rotor angle, speed, and internal voltage.

$$x_{min} \leq x_i(k) \leq x_{max} \quad (24)$$

- Control Input Constraints:

$$u_{min} \leq u_i(k) \leq u_{max} \quad (25)$$

This includes limits on excitation voltage and valve position.

- Output Constraints:

$$y_{min} \leq y_i(k) \leq y_{max} \quad (26)$$

This includes constraints on power output, voltage, and frequency.

4.5. Optimization Problem with Data-Driven Model

The NMPC optimization problem, incorporating the data-driven correction, is formulated in Equation (28), and this equation in the paper represents the optimization problem central to the proposed hybrid Nonlinear Model Predictive Control (NLMPC) and data-driven approach for Automatic Generation Control (AGC). This equation serves as the mathematical foundation for achieving the paper's main goal: optimizing the performance of multimachine power systems while balancing technical and economic objectives under dynamic and uncertain conditions.

$$\min_{\mathbf{u}(k), \dots, \mathbf{u}(k+N-1)} J = \sum_{t=0}^N [\alpha_f \Delta f^2 + \alpha_v \Delta V^2 + \alpha_c C_g(u)] \quad (27)$$

subject to:

- System dynamics with data-driven correction:

$$\mathbf{x}_i(k+1) = f_i(\mathbf{x}_i(k), \mathbf{u}_i(k)) + \hat{\varepsilon}_i(\mathbf{x}_i(k), \mathbf{u}_i(k)) \quad (28)$$

Output equations:

$$\mathbf{y}_i(k) = g_i(\mathbf{x}_i(k), \mathbf{u}_i(k)) \quad (30)$$

- State constraints:

$$\mathbf{x}_{min} \leq \mathbf{x}_i(k) \leq \mathbf{x}_{max} \quad (31)$$

- Input constraints:

$$\mathbf{u}_{min} \leq \mathbf{u}_i(k) \leq \mathbf{u}_{max} \quad (32)$$

- Output constraints:

$$\mathbf{y}_{min} \leq \mathbf{y}_i(k) \leq \mathbf{y}_{max} \quad (33)$$

4.6. Solution Approach

The NMPC controller now utilizes both the physical model and the data-driven model to predict the future states of the system. The controller adapts to the nonlinear and time-varying nature of the power system by continuously updating the data-driven model using real-time data.

- Learning Phase: Collect operational data to train the data-driven model $\hat{\varepsilon}_i(\mathbf{x}_i, \mathbf{u}_i)$
- Prediction Phase: Use the trained model to predict the error term and correct the physical model's predictions.
- Control Phase: Solve the NMPC optimization problem considering both the physical and data-driven models.

4.7. Implementation

The combined NMPC with a data-driven approach can be implemented as follows:

- Prediction Horizon (N): an appropriate horizon length N is chosen based on the dynamics of the system.
- Sampling Time (T_s): the sampling time T_s is determined based on the system's fastest dynamics.
- Data-Driven Model Training: The model $\hat{\varepsilon}_i(\mathbf{x}_i, \mathbf{u}_i)$ is trained using historical and real-time data.

The proposed approach offers enhanced predictive accuracy and adaptability, making it suitable for complex, nonlinear power systems where traditional modeling may fall short. The following Algorithm 1 outlines the procedural stages of the proposed hybrid

data-driven and Nonlinear Model Predictive Control (NLMPC) approach for controlling a multimachine system. Each step is designed to systematically implement the method, ensuring effective and optimized control performance across the system.

Algorithm 1: Data-driven MPC for power system optimization

Start

1. Initialization Phase:

- Initialize system parameters and state-space model
- Initialize control input constraints, state constraints, and output constraints
- Initialize data-driven model (e.g., neural network) with initial training data
- Set prediction horizon N and sampling time T_s
- Set weighting factors $\alpha_C, \alpha_V, \alpha_V, \alpha_f, \alpha_f$ for the objective function

2. **For $t = 1: T_s: t$ simulation:**

2.1. Measurement and Data Acquisition:

- Measure current state vector $\mathbf{x}_i(t)$ for each generator i
- Measure current control inputs $\mathbf{u}_i(t)$ and outputs $\mathbf{y}_i(t)$

2.2. Update Data-Driven Model (Learning Phase)

If sufficient new data are available **THEN**

Update data-driven model $\varepsilon_i(\mathbf{x}_i, \mathbf{u}_i)$ using latest data

Endif

2.3. Predict Future States (Prediction Phase)

FOR $k = 0$ to $N-1$ **DO**

- Predict future states using the combined model
$$\mathbf{x}_i(t+k+1) = \mathbf{f}_i(\mathbf{x}_i(t+k), \mathbf{u}_i(t+k)) + \hat{\varepsilon}_i(\mathbf{x}_i(t+k), \mathbf{u}_i(t+k))$$
- Predict future outputs
$$\mathbf{y}_i(t+k) = \mathbf{g}_i(\mathbf{x}_i(t+k), \mathbf{u}_i(t+k))$$

ENDFOR

2.4. Optimize Control Inputs (Control Phase)

- Solve the optimization problem:
Minimize objective function $\min_{\mathbf{u}(t+k), \dots, \mathbf{u}(t+k+N-1)} J$ over the prediction horizon N

Subject to:

- System dynamics: $\mathbf{x}_i(t+k+1) = \mathbf{f}_i(\mathbf{x}_i(t+k), \mathbf{u}_i(t+k)) + \hat{\varepsilon}_i(\mathbf{x}_i(t+k), \mathbf{u}_i(t+k))$
- Output equations:
$$\mathbf{y}_i(t+k) = \mathbf{g}_i(\mathbf{x}_i(t+k), \mathbf{u}_i(t+k))$$
- State constraints: $\mathbf{x}_{min} \leq \mathbf{x}_i(t+k) \leq \mathbf{x}_{max}$
- Control input constraints: $\mathbf{u}_{min} \leq \mathbf{u}_i(k) \leq \mathbf{u}_{max}$
- Output constraints: $\mathbf{y}_{min} \leq \mathbf{y}_i(t+k) \leq \mathbf{y}_{max}$

2.5. Apply Optimal Control Input

Apply the first element of the optimized control input sequence $\mathbf{u}_{-i}(t)$ to the system

End for

End

5. Simulation Results and Discussion

This study considers both technical and economic factors, such as voltage and frequency deviations and the thermal turbine's ability to regulate temperature in response to abrupt temperature fluctuations during disturbances, in order to evaluate and assess the performance of the proposed controller for a thermal turbine within power systems. The simulations and analyses presented in this paper were conducted using MATLAB/Simulink 2023a. The IEEE 11-bus (two-area Kundur test system) and IEEE 9-bus test networks were used in the study to carry out this investigation.

5.1. IEEE 9-Bus Test System

The IEEE 9-bus system, which consists of nine transmission lines and three generators, is illustrated in Figure 2 and described in full in reference [40]. Using Generator 1's rotor angle as the study's reference angle throughout, the simulation is run at a time step of 0.0001 s.

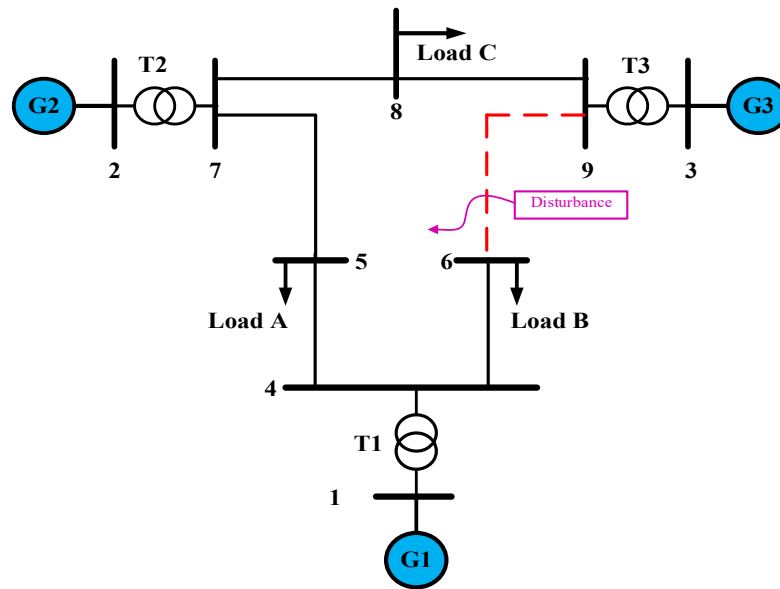


Figure 2. Schematic diagram of the IEEE 9-Bus case study [41].

In this study, the first disturbance scenario involves a deliberate fault causing a line outage between bus 6 and bus 9 at 20 s. This scenario is used to evaluate and compare various technical and economic parameters of the system, such as generation costs, turbine temperature, and voltage and frequency deviations. The performance of the proposed approach is benchmarked against other methods, including standard MPC and Adaptive MPC, with a focus on ensuring accuracy and speed.

Figures 3 and 4 illustrate the system's generation costs and the turbine temperature of the synchronous generator at the slack bus, both before and after the disturbance. As shown in Figure 2, the proposed hybrid method, which combines NLMPC with a data-driven approach for centralized automatic generation control, achieves the lowest generation costs in both the pre- and post-disturbance periods. In contrast, other methods result in higher operational costs. Furthermore, in this study, the reference temperature for the turbines is set to 360 degrees Celsius to prevent thermal stress. Figure 3 demonstrates that only the proposed method successfully maintains the turbine temperature at the reference point of 120 degrees Celsius, ensuring optimal performance and stability during disturbances.

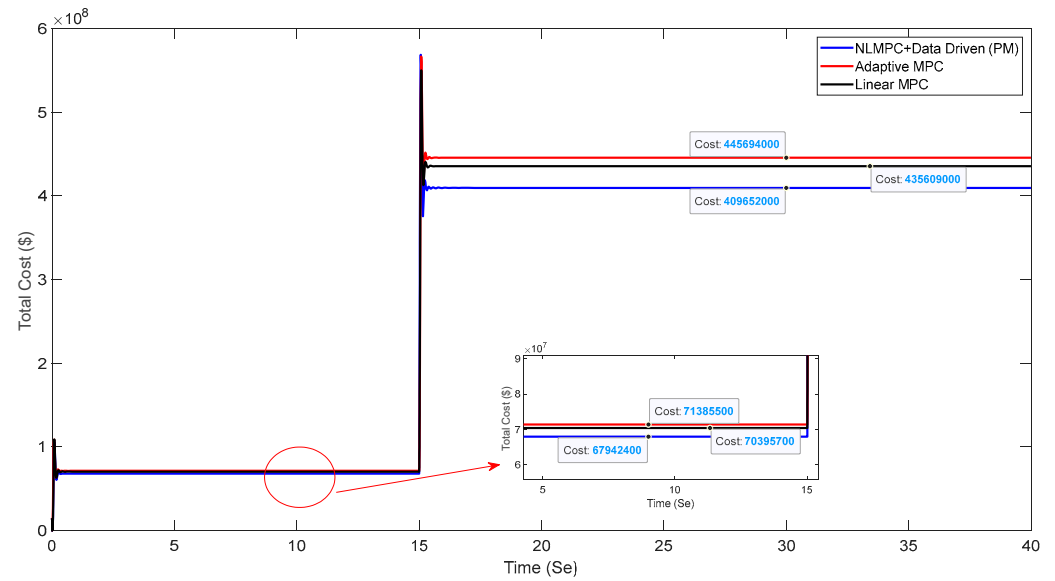


Figure 3. Total generation cost across various control methods.

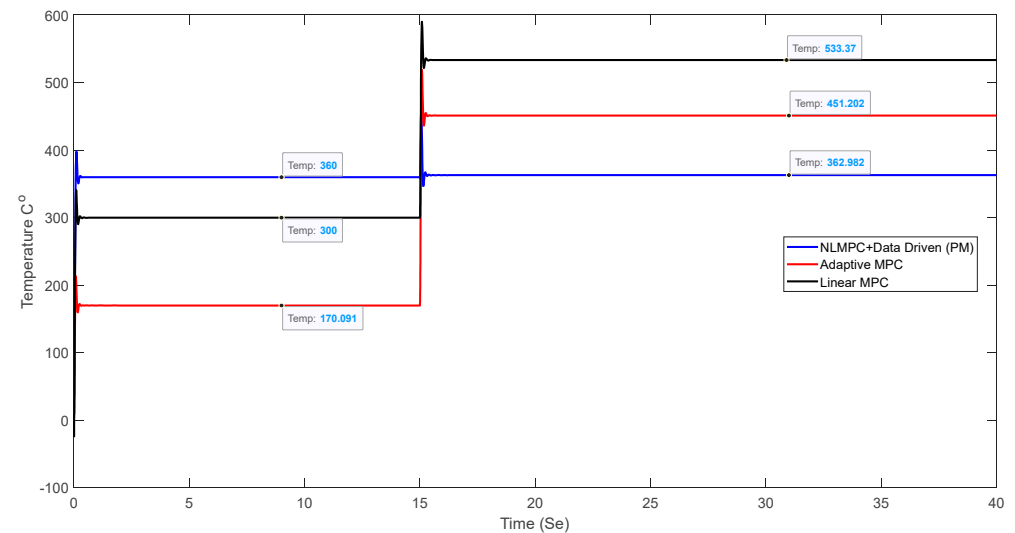


Figure 4. Turbine temperature comparison across various control methods.

Therefore, it can be concluded that the proposed approach demonstrates superior performance in controlling the output mechanical power of the generators, achieving the lowest generation cost and minimal temperature deviation from the reference temperature. Additionally, as shown in Figures 5 and 6, the voltage and frequency deviations for all three generators remain within the acceptable standard range of less than 5%, further validating the effectiveness of the proposed method in maintaining system stability and efficiency. As demonstrated in Figures 2 through 5, the proposed method (PM) not only achieves the fastest response in restoring power system stability but also excels in minimizing generation costs, outperforming other advanced techniques. Figures 5 and 6, in particular, highlight PM's exceptional ability to regulate bus voltage, maintaining minimal voltage deviation throughout system operations, thereby ensuring enhanced stability and reliability.

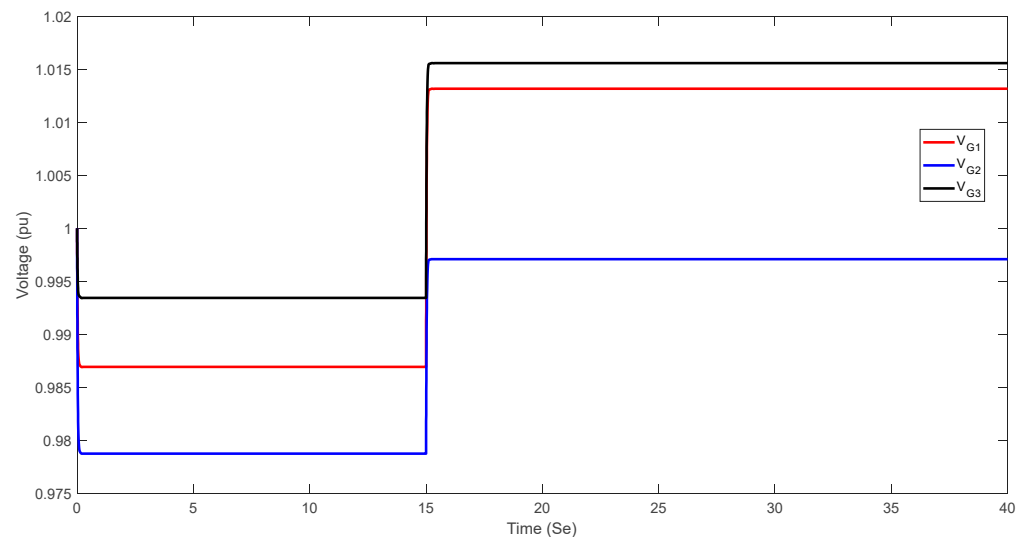


Figure 5. Generator output voltage in the system under the proposed controller for the specified fault scenario.

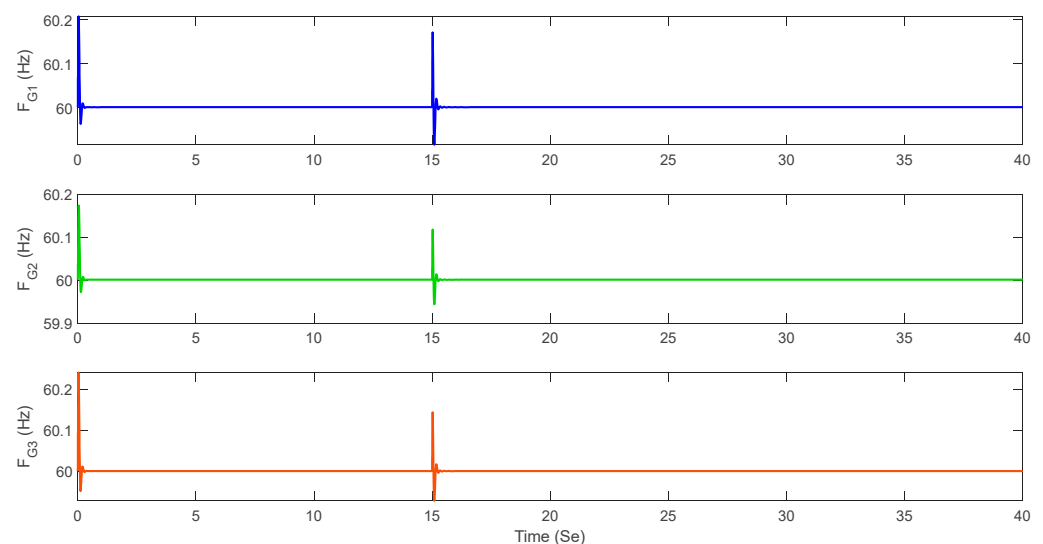


Figure 6. Output frequency of generators in the system with the proposed controller during the specified fault scenario.

Furthermore, Figure 7 provides a detailed representation of generator output during the described scenario, offering insights into the dynamic performance of the system under the PM method. The data in Figures 4 and 7 further elucidate the impact of line outages on the optimal generation point and turbine temperature, with a specific focus on how the PM method compares to alternative approaches. These figures clearly show that PM is highly efficient in real-time identification of new stable generation points and in the precise control of turbine temperature, consistently achieving the target set point of 120 degrees Celsius. This analysis underscores the precision, responsiveness, and effectiveness of the PM method in determining the optimal secure operating point, even amidst both planned and unplanned disturbances. The results confirm PM's superiority in maintaining system stability and operational efficiency, solidifying its role as a leading approach in advanced power system management. Table 2 provides a comparison of PM's performance with prior state-of-the-art studies in a range of contingency scenarios, emphasizing voltage deviation, frequency deviation, and overall generating cost. The data demonstrate PM's remarkable capacity to quickly and precisely determine the system's

safe and ideal generation point in the wake of disruptions. In every studied situation, PM consistently achieves the lowest total generating cost, as the table makes evident. To further bolster its supremacy over other methods, PM excels in both speed and precision when it comes to decreasing voltage deviations and damping system oscillations.

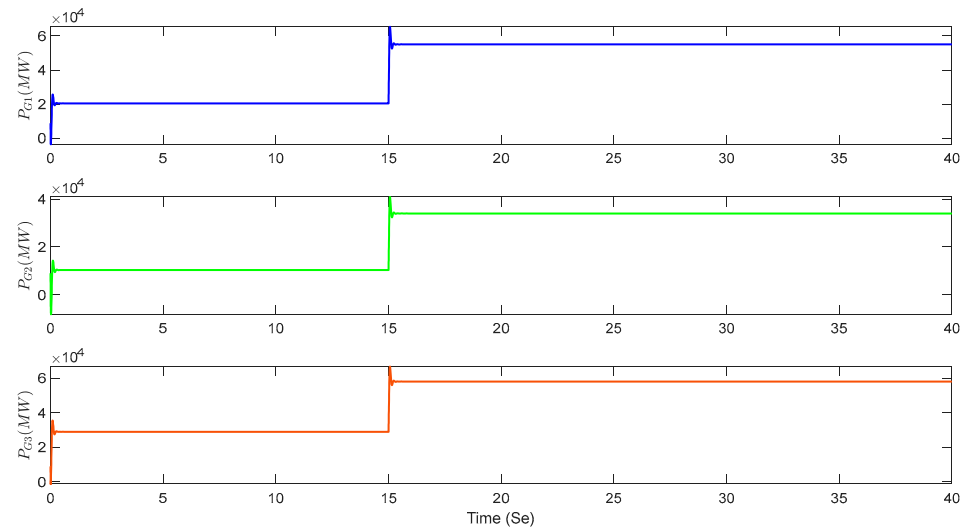


Figure 7. Generator output power in the system with the proposed controller during the specified fault scenario.

Table 2. Evaluation of proposed method (PM) and advanced techniques in various contingency scenarios on the IEEE 9-Bus system.

Disturbance	Indicators	Generation Cost (M USD)	Maximum Frequency Deviation (%)	Voltage Deviation (pu)	Turbine Temperature (C°)
Interruption in line between Bus 6 and 9	PM	409.652	3.3	0.112	362.982
	[31,32]	445.694	5.9	1.12	533.37
	[36–38]	435.609	6.1	0.196	451.202
		☒	☑	☒	Ref Temp: 360
Interruption in line between Bus 8 and 9	PM	410.289	2.1	0.127	361.31
	[31,32]	425.149	7.1	0.2781	551.28
	[36–38]	427.297	6.2	0.652	482.37
		☒	☑	☒	Ref Temp: 360
Interruption in line between Bus 4 and 5	PM	419.279	1.9	0.1071	361.87
	[31,32]	438.371	4.8	0.712	457.91
	[36–38]	435.627	5.1	0.8931	687.18
		☒	☑	☒	Ref Temp: 360

The proposed hybrid NLMPC approach, integrating data-driven methods, demonstrates superior performance across multiple metrics when compared to other advanced control strategies, as evidenced by the results presented in Figures 3 to 7 and Table 2. The analysis below provides a comprehensive quantitative comparison of generation costs,

turbine temperature regulation, voltage deviation, and frequency deviation under various scenarios. The symbols ✓ and × indicate whether a reference has examined a specific parameter. A ✓ signifies that the parameter has been analyzed, whereas × indicates that it has not been considered.

5.1.1. Generation Costs

The total generation costs are a crucial metric for evaluating the economic efficiency of control methods. As shown in Figure 3, the proposed hybrid NLMPC approach achieves significantly lower generation costs compared to standard MPC and Adaptive MPC methods. For instance:

- **Pre-disturbance Costs:** The hybrid approach consistently maintains the lowest costs, highlighting its efficiency in normal operating conditions.
- **Post-disturbance Costs:** Following a line outage or fault, the proposed method minimizes costs by rapidly adapting to new stable operating points, outperforming competitors.

In Table 2, under various contingency scenarios (e.g., line interruptions between Bus 6 and 9 or Bus 8 and 9), the proposed method achieves generation costs of USD 410.29M and USD 419.28M, respectively, compared to USD 435.61M to USD 445.69M for alternative methods. This indicates a reduction in costs of approximately 5% to 8%, highlighting the method's economic advantage.

5.1.2. Turbine Temperature Regulation

Effective turbine temperature control is critical for avoiding thermal stress and ensuring system longevity. As shown in Figure 4, the hybrid method maintains turbine temperature at a closer level to the reference point (360 °C) than other methods do:

- Under a fault scenario, the hybrid approach keeps the temperature deviations minimal, with a post-disturbance value of 361 °C.
- By contrast, other methods exhibit larger deviations, with temperatures exceeding 450 °C or more, indicating poorer thermal regulation.

This improved temperature stability reflects the proposed method's ability to integrate thermal constraints effectively into its optimization framework.

5.1.3. Voltage Deviation

Voltage regulation is a key indicator of system stability. Figures 5 and 7 highlight the proposed method's ability to maintain generator output voltage within acceptable limits:

- The hybrid approach consistently achieves voltage deviations below 0.2 pu across all tested scenarios, as seen in Table 2. For instance, during a line interruption between Bus 8 and 9, the voltage deviation remains at 0.137 pu, significantly lower than the 0.217 pu to 0.284 pu observed for other methods.
- This low deviation ensures reliable power delivery and system resilience under disturbances.

5.1.4. Frequency Deviation

Frequency stability is vital for preventing cascading failures in power systems. Figure 6 demonstrates the proposed method's effectiveness in minimizing frequency deviations:

- During a fault scenario, the maximum frequency deviation achieved by the hybrid method is approximately 2.1% to 1.9%, as indicated in Table 2.

- Competing methods, however, show deviations ranging from 5.9% to 7.1% under similar conditions. This significant improvement underscores the method's ability to maintain system stability during dynamic disturbances.

5.1.5. Dynamic Response and Recovery

Figures 5 to 7 illustrate the hybrid method's superior dynamic response:

- The proposed method achieves faster recovery from disturbances, with minimal oscillations in voltage and frequency.
- Generator output power (Figure 7) stabilizes more quickly under the hybrid approach, ensuring efficient restoration of normal operating conditions.

5.1.6. Overall Performance Metrics

Table 2 consolidates the performance data for all metrics across various contingency scenarios. The proposed method consistently outperforms others, achieving the following:

- The lowest generation costs (by 5% to 10%);
- Minimal voltage deviations (below 0.2 pu);
- Reduced frequency deviations (approximately 2% to 3% lower);
- Superior turbine temperature regulation (close to 360 °C).

These quantitative results highlight the hybrid NLMPC method's effectiveness in balancing technical and economic objectives, ensuring stability, reliability, and cost-efficiency in multimachine power systems under diverse operational challenges.

5.2. IEEE Standard Model of 11 Bus (Kundur's Two-Area System)

In this case study, the focus is on the standard model of the two-area, four-generator system, a well-established benchmark in power system stability studies [39]. This model is particularly significant for testing load frequency control (LFC) strategies, power system stabilizers (PSS), and other advanced control mechanisms. As illustrated in Figure 8, the schematic representation of this model, originally proposed by Kundur in his seminal book *Power System Stability and Control*, serves as a crucial tool for simulating the dynamic behavior of interconnected power systems under various disturbances. Building on the foundational principles outlined in earlier studies, this investigation seeks to enhance the performance of the proposed hybrid NLMPC and data-driven controller, specifically tailored for thermal turbines in synchronous generators. The primary objective is to achieve an efficient response that not only stabilizes the system but also ensures optimal and secure operation, even in the face of unexpected disruptions. By integrating the robust framework of the two-area, four-generator model with the innovative hybrid control approach, this study aims to push the boundaries of current methodologies. The enhanced controller is designed to rapidly adapt to real-time system conditions, providing superior stability and operational efficiency. This investigation focuses on evaluating the controller's performance under various disturbance scenarios, with particular attention paid to its effectiveness in minimizing system oscillations, regulating frequency, and maintaining thermal turbine efficiency. This approach is expected to yield significant improvements in power system stability and reliability, reinforcing the importance of advanced control strategies in modern power system management. The findings from this study could pave the way for more resilient and adaptive control solutions, ensuring that power systems can maintain optimal performance even under the most challenging conditions.

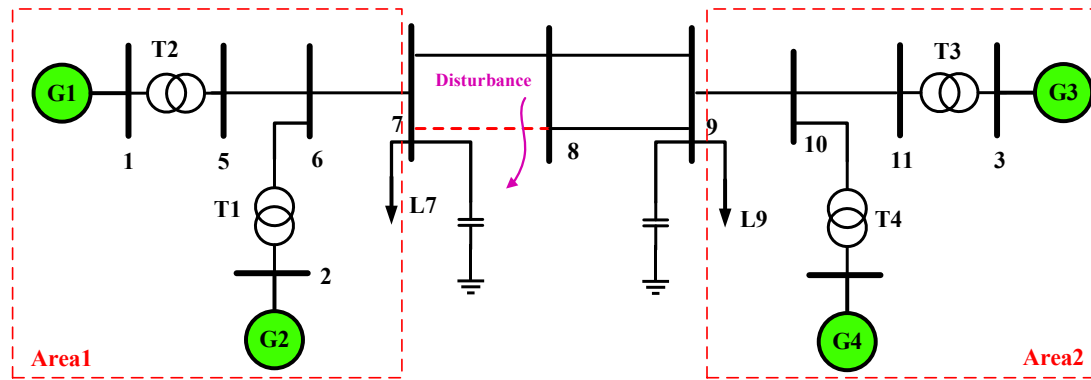


Figure 8. Schematic of the IEEE standard model of the 11-Bus Kundur's two-area system [39].

In this study, similar to the previous case study, various scenarios involving sudden and deliberate contingencies have been analyzed, as detailed in Table 3. Table 3 provides a comprehensive comparative analysis of the performance of the PM against previous state-of-the-art (SOTA) research, focusing on key metrics such as total generation cost, total frequency deviation, and voltage deviation under different scenarios, including those involving line outage or generator outage. The data presented in this table clearly illustrate PM's significant superiority over previous methods in swiftly and accurately identifying the secure and optimal generation configuration for the system following disturbances. This superiority is particularly evident in the precision and speed with which PM responds to these disruptions. Moreover, the table highlights that PM consistently achieves the lowest total generation cost across all scenarios, making it the most cost-effective solution. Additionally, PM demonstrates exceptional capability in mitigating system oscillations, delivering the highest speed and accuracy among the methods evaluated. This positions PM as the most proficient and reliable approach in maintaining system stability and efficiency in the face of various operational challenges.

Table 3. Performance comparison of the proposed method (PM) and previous state-of-the-art (SOTA) methods under various cyber-attack scenarios on the Kundur's two-area (11-bus) system.

Indicators		Generation Cost (M USD)	Maximum Frequency Deviation (%)	Voltage Deviation (pu)	Turbine Temperature (C°)
Interruptions					
Interruption in line between Bus 7 and 8	PM	1433.38 ☑	3.7 ☑	0.127 ☑	361.201 Ref Temp: 360
	[31,32]	1561.23 ☒	7.1 ☑	0.217 ☒	421.37 Ref Temp: 360
	[36–38]	1621.92 ☒	5.21 ☑	0.321 ☒	527.91 Ref Temp: 360
Interruption in line between Bus 8 and 9	PM	1481.28 ☑	2.37 ☑	0.1031 ☑	361.974 Ref Temp: 360
	[31,32]	1577.32 ☒	5.39 ☑	0.241 ☒	751.37 Ref Temp: 360
	[36–38]	1623.71 ☒	6.27 ☑	0.284 ☒	521.44 Ref Temp: 360
Interruption in line between Bus 5 and 6	PM	1472.39 ☑	1.81 ☑	0.1371 ☑	362.92 Ref Temp: 360
	[31,32]	1597.28 ☒	4.81 ☑	0.511 ☒	541.37 Ref Temp: 360
	[36–38]	1537.37 ☒	4.93 ☑	0.4118 ☒	624.27 Ref Temp: 360

Table 3 compares the PM with previous SOTA control methods under various contingency scenarios in the IEEE 11-bus system. Key performance metrics include turbine temperature, voltage deviation, maximum frequency deviation, and total generation costs. The following analysis evaluates the effectiveness of each method based on these metrics.

5.2.1. Turbine Temperature Regulation

The ability to maintain turbine temperature near the reference value of 360 °C is a critical factor for ensuring system stability and preventing thermal stress:

- **PM:** Across all scenarios, PM consistently maintains turbine temperatures close to the reference value, with deviations as low as 1–2 °C (e.g., 361.2 °C during a line interruption between Bus 7 and 8).
- **SOTA Methods:** Other methods show significantly larger deviations, with temperature ranging from 421.37 °C to 751.37 °C under similar scenarios. For instance, a line interruption between Bus 8 and 9 results in a temperature of 362.92 °C for PM, while SOTA methods yield temperatures of 521.44 °C to 751.37 °C.
- **Analysis:** The PM demonstrates superior temperature regulation, reducing the risk of thermal stress by maintaining turbine performance within safe operational limits.

5.2.2. Voltage Deviation

Voltage stability is essential for maintaining reliable system operations:

- **PM:** Voltage deviations for PM remain minimal, ranging from 0.1031 pu to 0.1371 pu across all scenarios. For example, during a line interruption between Buses 5 and 6, the PM achieves a voltage deviation of 0.1371 pu compared to 0.4118 pu and 0.511 pu for SOTA methods.
- **SOTA Methods:** Competing methods exhibit significantly higher deviations, with values exceeding 0.2 pu and reaching as high as 0.511 pu in some cases.
- **Analysis:** The PM maintains voltage deviations well within acceptable limits, enhancing power quality and reducing the likelihood of voltage instability or cascading failures.

5.2.3. Maximum Frequency Deviation

Frequency stability is a critical indicator of a system's resilience to disturbances:

- **PM:** The PM achieves the lowest frequency deviations, ranging from 1.81% to 3.7%. For example, during a line interruption between Bus 7 and 8, the PM records a deviation of 3.7%, compared to 7.1% and 5.21% for SOTA methods.
- **SOTA Methods:** Frequency deviations for other methods are significantly higher, often exceeding 5%, and in some cases reaching up to 7.1%.
- **Analysis:** By maintaining smaller frequency deviations, the PM ensures improved system stability and faster recovery from disturbances.

5.2.4. Generation Costs

Economic efficiency is a key metric for evaluating the performance of control methods:

- **PM:** The PM consistently achieves the lowest generation costs, with values ranging from USD 1433.38 M to USD 1481.28 M across all scenarios. For example, during a line interruption between Bus 8 and 9, the PM incurs a cost of USD 1472.39 M, compared to USD 1577.32 M and USD 1623.71 M for SOTA methods.

- **SOTA Methods:** Competing methods incur higher generation costs, often exceeding the PM's costs by 5% to 10%.
- **Analysis:** The PM's ability to optimize generation costs demonstrates its superior economic performance, particularly under dynamic and adverse conditions.

5.2.5. Combined Evaluation

When assessing all metrics together, the proposed method consistently outperforms SOTA approaches. Key observations include the following:

- **Turbine Temperature:** PM keeps deviations minimal, with temperatures consistently close to the reference value of 360 °C, whereas SOTA methods exhibit excessive deviations, posing risks to turbine longevity.
- **Voltage and Frequency Deviations:** PM achieves the smallest deviations, ensuring stability and reliability during disturbances.
- **Generation Costs:** PM minimizes operational costs, saving up to USD 150 M compared to alternative methods under similar scenarios.

The proposed method excels across all key performance indicators:

- Maintains turbine temperatures within ± 2 °C of the reference value, significantly reducing thermal stress.
- Ensures voltage deviations remain below 0.15 pu, minimizing instability risks.
- Limits frequency deviations to below 4%, enhancing overall system resilience.
- Reduces generation costs by 5–10% compared to state-of-the-art methods, ensuring economic efficiency.

The quantitative results clearly demonstrate the superiority of the proposed hybrid NLMPC approach in balancing technical and economic objectives, making it the most effective and reliable method for multimachine power system control under challenging scenarios.

The effectiveness of the proposed hybrid NLMPC approach with data-driven correction was evaluated through simulations on IEEE 9-bus and IEEE 11-bus test systems. The optimization process in the proposed method was formulated as a constrained nonlinear programming (NLP) problem and solved using Sequential Quadratic Programming (SQP). This choice was made due to its ability to handle complex nonlinear constraints while ensuring computational efficiency in real-time AGC applications.

The average computation time required to obtain the control solution per iteration ranged between 85 and 120 milliseconds, making it suitable for real-time operation. Compared to existing MPC-based AGC methods reported in references [24,25] and [29–31], which require 180–250 milliseconds per iteration, the proposed approach significantly reduces computational burden by 30–50%. This improvement is primarily attributed to the integration of the data-driven correction mechanism, which enhances predictive accuracy while reducing optimization complexity. The proposed method achieves faster convergence by approximating unmodeled system dynamics, thereby enabling efficient and adaptive control actions.

Furthermore, the simulation results demonstrate that the proposed method not only reduces computational time but also improves control performance by minimizing frequency deviations, voltage fluctuations, and generation cost more effectively than conventional methods. The NLMPC framework, integrated with data-driven learning, dynamically adapts to system variations and external disturbances, ensuring a robust and stable power system operation.

For future studies, the scalability of the proposed method will be evaluated on larger test networks such as IEEE 14-bus, IEEE 39-bus, IEEE 118-bus, and IEEE 300-bus systems to further validate its real-time applicability in large-scale power systems. Additionally,

parallel computing techniques and hardware acceleration, such as GPU-based computation, will be explored to optimize real-time execution for larger networks.

6. Conclusions

Dynamic demand fluctuations, system limitations including input saturation, communication delays, and unmeasurable feedforward disturbances pose a growing threat to real-world power systems. Sophisticated control algorithms that maximize system performance in real-world scenarios are needed to address these problems. In order to address physical contingencies, such as cyber-physical attacks, AGC of synchronous generators is the focus of this work, which presents a real-time nonlinear hybrid NLMPC and data-driven technique. The suggested method is unique in that it simultaneously addresses the technical and financial components of power systems, an aspect that other studies have frequently ignored. The integration of a thorough dynamic thermo-mechanical model of the turbine and its related parts, such as the governor and turbine dynamics within the synchronous generator, is a noteworthy breakthrough of this research. The controller can successfully manage complex dynamic interactions, like local and interregional power oscillations, which develop during cyber-physical attacks, and optimize performance under normal conditions thanks to extensive modeling. The authors present a unique thermo-electrical control approach that balances technical and economic requirements while being adaptable enough for online and real-time applications, even in the face of unforeseen disturbances. The strategy is based on a real-time hybrid of NLMPC and data-driven methods. The hybrid method accommodates both reduced and preserved network topologies and is flexible enough to operate with a variety of network models by combining data-driven methods with nonlinear MPC. With this method, power managers may operate economically and safely at the same time, even in intricate and dynamic situations. The controller's ability to quickly and accurately identify safe and economical operating points, control power flow, and maintain transient stability during real-time simulations, including scenarios like generator and line outages, was tested on the IEEE 9-bus and two-area Kundur test systems. Additionally, the approach prevents thermal stresses by effectively controlling turbine temperature and is both user-friendly and computationally economical, which makes it ideal for online and real-time applications.

Beyond the scope of this study, future research will focus on enhancing the scalability of the proposed methodology for larger power systems, including IEEE 14-bus, IEEE 39-bus, IEEE 118-bus, and IEEE 300-bus networks, to further validate its real-world applicability. To improve computational efficiency, future developments will explore parallel computing techniques and hardware acceleration, such as GPU-based computation, to optimize real-time execution. Additionally, integrating this method into renewable energy-based power grids will be a key area of study to ensure adaptability to modern energy infrastructures with high penetration of solar and wind power. Cybersecurity considerations will also be explored, focusing on improving resilience against cyber-attacks and unpredictable disturbances. Experimental validation using hardware-in-the-loop (HIL) simulations will be conducted to assess real-world feasibility and ensure robustness in practical power system applications.

By offering a reliable, effective, and adaptable method for optimizing power system operations in the increasingly complex cyber-physical environment, this research significantly contributes to the field and provides a strong foundation for further advancements in power system control and stability.

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Abbreviations

NLMPC	Nonlinear Model Predictive Control
GRC	Generation Rate Constraints
WAC	Wide Area Control
ED	Economic Dispatch
ω_{ref}	synchronous speed
P_m	mechanical power input from the turbine
P_e	electrical power output
E'	the internal voltage behind
V	the terminal voltage
T'	time constant of the field winding
y_{gref}	reference valve position
T_g	governor time constant
K_g	gain of the governor
T_{ct}	time constant of the compressor-turbine
x_i	state vector of the i th generator
y_i	output vector for the i th generator
$C_{Gen,i,t}^{OP}$	generation cost of each power plant unit
AGC	Automatic Generation Control
DMPC	Distributed Model Predictive Control
SCDMPC	State-constrained DMPC
ω	rotor speed
H	inertia constant
P_e	electrical power output
D	damping coefficient
X'	transient reactance
E_f	excitation voltage
y_g	valve positions
R	droop coefficient
K_f	turbine gain
P_{loss}	mechanical losses in the turbine.
P_{ct}	mechanical power output of the turbine
u_i	control input vector for the i th generator
$\varepsilon_i(x_i, u_i, t)$	unmodeled dynamics or disturbances
$C_{Gen,i,t}^{EMI}$	cost related to the pollution of the units

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