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Enhancing Micro grid Frequency Stability with EV-ESS Integration and Optimized Predictive Control

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Abstract: This paper explores the integration of electric vehicles (EVs) with energy storage systems (ESS) to enhance frequency regulation in isolated micro grids facing challenges from renewable energy variability and load fluctuations. Due to the high cost and degradation issues of ESS, leveraging EVs as supplementary storage offers a cost-effective and reliable solution. A Model Predictive Control (MPC) strategy is proposed to manage both ESS and EVs dynamically in response to frequency deviations. To improve control performance, Grey Wolf Optimization (GWO) is employed to fine-tune the MPC parameters. Simulation results using MATLAB/Simulink validate the effectiveness of the proposed method in maintaining frequency stability under various operating conditions.
Keywords: *Microgrid, Frequency Stability, Electric Vehicles (EV,) Predictive Control.*

1. Introduction

With the rapid growth of electric vehicle (EV) adoption, distribution system operators (DSOs)—responsible for the stability and availability of medium and low voltage distribution grids—face increasing pressure to manage grid congestion. The surge in EV charging demand is expected to bring low-voltage networks closer to their operational limits [1,2]. Congestion occurs when infrastructure components such as transformers or distribution lines operate near capacity, risking failure. These critical areas, referred to as *congestion points*, are safeguarded by protective mechanisms like fuses, which, while ensuring safety, can also increase stress on surrounding infrastructure.

To prevent such overloads and ensure grid reliability, DSOs can leverage *energy flexibility* through congestion management strategies. These approaches, often driven by pricing mechanisms and market-based controls, help shift or reduce load during peak periods. Power scheduling aggregators, which coordinate energy interactions within a portfolio of users and flexible loads, can incorporate congestion constraints into their scheduling decisions. This allows them to support DSOs in actively managing grid stability. Figure 1 illustrates the distribution grid, highlighting both a detailed view of a single substation and its integration within the broader network. EVs are connected at various branches of the grid, each of which can act as a congestion point. The substation, representing the combined impact of these branches, can also face congestion, particularly under high load scenarios. For aggregators to effectively support congestion control, they must understand which flexibility providers (such as EVs or batteries) are connected to which congestion points. This is managed through *subsets*—groupings of flexibility providers linked to specific congestion areas [3]–[10].

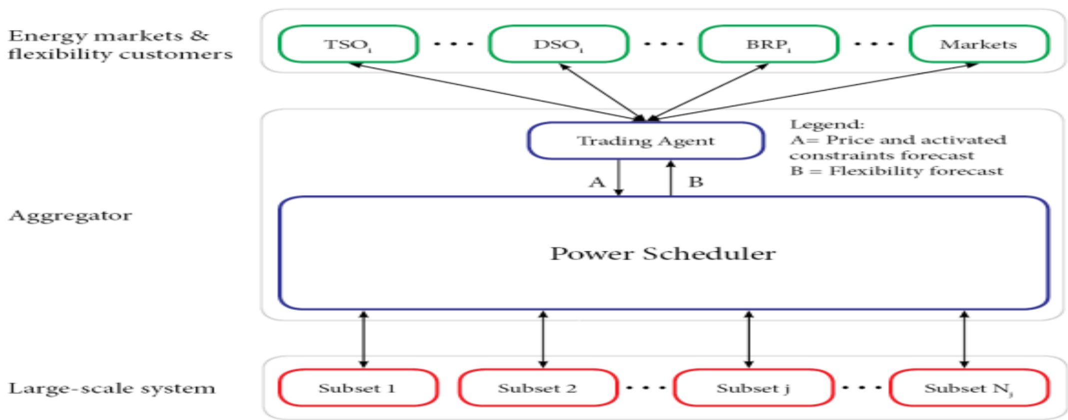

Figure 1: Schematic representation of the aggregator setting with respect to potential energy flexibility users and the EV fleet, which are divided over the subsets.

While many aggregator models in existing literature simplify the network by applying a single global constraint [6,7], this overlooks important spatial details. In reality, geographic and network topology information is crucial for accurate congestion management. By incorporating this spatial context, aggregators can provide more targeted and effective congestion control services to DSOs.

To maximize income, the aggregator negotiates with clients on how to best utilize available energy flexibility. This complex process is divided into two connected agents: the trading agent and the power scheduler (see Fig. 1). The trading agent handles negotiations with users and provides the power scheduler with forecasts on network constraints and electricity prices based on agreements. Network constraints specify allowable power use over time for individual or combined congestion points. The power scheduler then uses price forecasts to optimize the remaining flexibility and reduce costs [11]–[15].

II. Literature Review

Nguyen et al.[16] proposes a distributionally robust model predictive control (DRMPC) for energy management of a vehicle-to-grid (V2G)/vehicle-to-vehicle (V2V)-enabled smart electric vehicle charging station (EVCS) with a photovoltaic (PV) system and an energy storage system. To improve computational efficiency, a penalty method is proposed to relax the complementarity constraints, while still ensuring non simultaneous charging and discharging of EVs under the derived sufficient conditions.

Abdelghaffar et al.[17] outlines model predictive control (MPC) implementation to integrated onboard battery chargers (OBC) utilizing a multiphase EV-drive train. Unfortunately, as the number of phases increases, the adoption of MPC becomes more complex. Positively, the redundant phases facilitate the optimization of the control action. To transition between pre- and post-fault instances, the presented approach requires only a slight adjustment to the control mechanism.

Chai et al.[18] introduced a dual-phase optimization strategy to delineate the charging and discharging schedule of EVs involved in a vehicle-to-grid (V2G) initiative at a workplace facility. Their model prioritizes the commuting convenience of EV owners by presenting two distinct V2G options. The initial step involves day-ahead optimization (DAO). Leveraging anticipated building load patterns and EV user tendencies, this step aims to regulate EV charging or discharging optimally, with the overarching goal of trimming electricity expenses by curtailing the building's peak demand. Furthermore, the study delves deep into a thorough cost-effectiveness evaluation, shedding light on the potential fiscal advantages and incentives for both the infrastructure and the EV user when leveraging V2G to mitigate peak load .

In a study by Hou et al. [19], the energy management dynamics of a microgrid, integrating solar-hydrogen technologies, is explored. This comprehensive microgrid comprises zero-emission vehicles, green energy sources, an electrolyser, two-way charging infrastructures, and a hydrogen-based refuelling hub with storage capabilities. The unique advantage of the Vehicle-to-grid (V2G) stations is their capability to counterbalance the erratic nature of renewable energy by channelling vehicular battery energy back into the grid. Meanwhile, excess solar energy can be channelled by the electrolyser for supply-demand equilibrium through power-to-gas (P2G) operations. Amidst the unpredictability of renewable power generation and energy consumption, a bifurcated stochastic optimization blueprint is introduced. This aims for an ideal power regulation tactic across components to cut down on operational expenses. With this design, initial phases determine upcoming EV charging prices and hydrogen production energy allocations, while subsequent stages undertake real-time power allotment across various situations. After implementing this proposed model in a case study using genuine data, findings revealed an impressive potential to shrink daily operational charges by nearly 27.5%.

Zhang et al.[20] introduced a real-time Connected Electric Vehicle (CEV) framework that synergizes ride-sharing with dynamic V2G scheduling. The integrated issue is characterized as a mixed-integer quadratic programming (MIQP) challenge. Accounting for prediction variances, they create an online scheduling model which considers communication impacts on immediate reactions. Concurrently, a dual-tier system mechanism is shaped to harmonize CEV actions, utilizing Benders' decomposition. Through various case studies, it's evident that this model adeptly enables expansive urban ride-sharing and V2G modulation services via trustworthy vehicular communication channels. Furthermore, not only does the online dual-tier method boast reduced computational times across different network dimensions, but the coordinated use of CEVs also paves the way for a significant reduction in operational costs, slashing them by an estimated 43.71%, and fortifying urban grid resilience.

Mehsra et al.[21] focuses on the challenge to develop coordination between an electric vehicle (EV) charger, energy storage system (ESS), and smart charging/discharging strategy in a low-inertia grid-connected vehicle-to-grid system. Two smart bidirectional charging strategies are proposed to control EV and ESS for minimizing the frequency error by considering the EV constraints. A linear programming optimization algorithm with modified objective function is employed to design a smart charging technique for EVs. For ESS, three operating scenarios are assessed 1) without ESS, 2) with ESS, and 3) with ESS and considering the state of charge (SOC) drop. In the comprehensive charging strategy for ESS, the same LPOA designed for EV has been employed wherein EV SOC drop is observed to noticeably increase frequency regulation ability while the EV has a determined low SOC during a specified interval. The simulation results in MATLAB/SIMULINK environment validate the accuracy of these smart charging techniques.

RESEARCH METHODOLOGY

Extensive research has been done recently on the microgrid (MG) to confirm that it operates steadily and dependably. As was already noted, there are various MG types with various operating functions. An isolated MG is examined in this work to validate the effectiveness of several controllers for frequency regulation. Diesel generators (DG) and renewable energy sources (RES), such as wind farms and solar photovoltaic systems, are the primary energy sources. The prosumers are next introduced, including electric vehicles (EVs) and energy storage systems (ESS), before home loads are employed as the energy consumers, as demonstrated in Fig. 3.1. The whole structure of the isolated MG utilised for frequency regulation is shown in equation (1), while the following subsections provide comprehensive information on each part.

$$\underbrace{\Delta P_{DG}} + \underbrace{\Delta P_{PV} + P_{Wind}} \mp \underbrace{\Delta P_{EV} \mp P_{ESS}} - \Delta P_L = \underbrace{M.S + D} \quad .\Delta f \qquad (1)$$

RENEWABLE ENERGY RESOURCES

Everywhere in the world, there is access to solar and wind energy. In order to generate electricity, solar photovoltaic (PV) systems and wind turbine systems (WTS) are frequently employed. An array of PV cells, a converter to raise DC voltages, and an inverter to obtain the necessary AC voltages make up the PV system, which converts sunlight into DC electricity [30]. Solar irradiation, PV panel voltage and current, and PV cell temperature all affect how much PV electricity is produced [31]. The solar PV system is the first option among the RERs to be deployed in remote areas because to its simplicity of installation and abundant sun irradiance.

The output PV (PPV) can be calculated by eq. (2):

$$P_{PV} = \varphi.\theta.S.\left(1 - 0.005(T_A - 25)\right)(2)$$

where ψ, ϕ and S is the irradiance, conversion efficiency, and effective area of the solar array. While TA is ambient temperature.

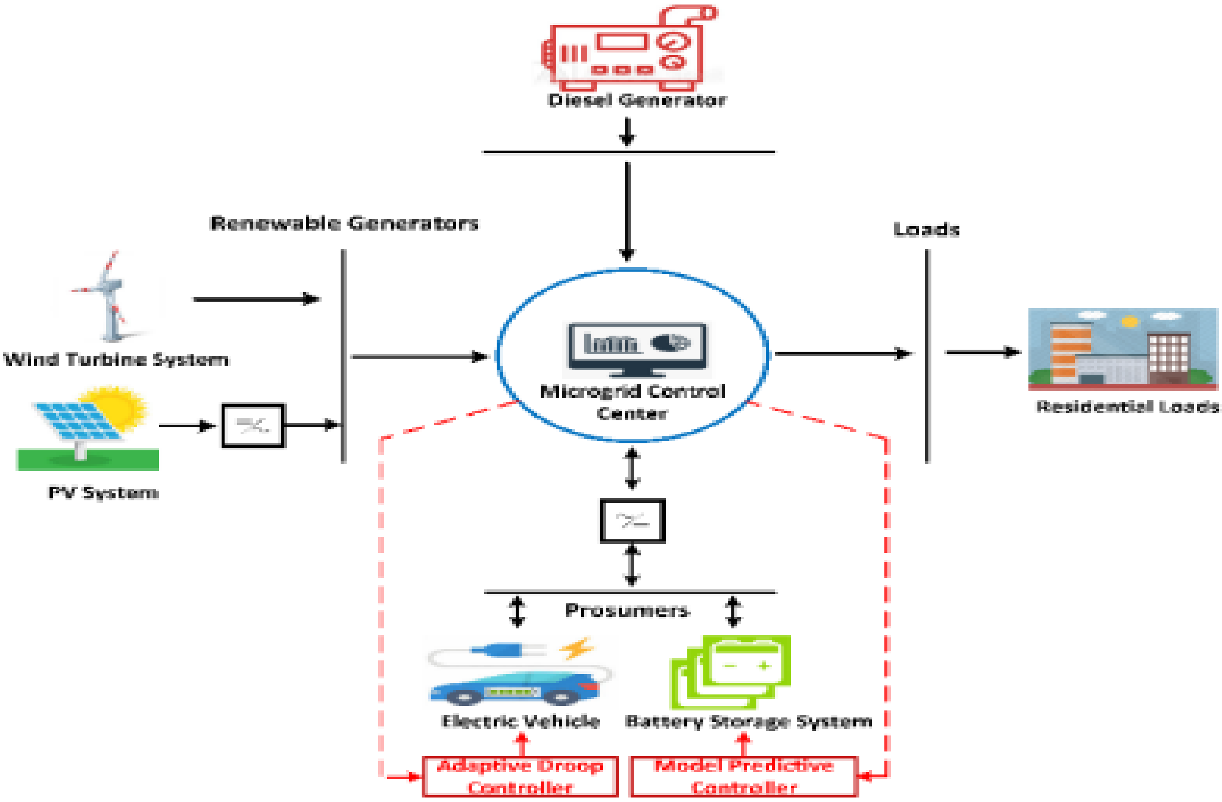

Figure 2.The isolated micro grid dynamic model.

THE PROPOSED CONTROL SYSTEM DESIGN

3.2.1. THE PROBLEM FORMULATION

In this study, a single MG is examined to see how ESS and EVs affect the frequency regulation of the MG. While an MPC controller is used to regulate the output of the energy storage system (ESS) in accordance with the system frequency deviation, adaptive droop control (ADC) is a technique for controlling the regulation of an electric vehicle's battery (EVB). Additionally, in order to find the best solution, Gray wolf optimization(GWO) is used on the MPC and ADC parameters.

3.2.2 FUZZY LOGIC PI CONTROLLER

To compare their performance to that of the model predictive controller (MPC), the proportional-integral (PI) and fuzzy logic PI (FPI) controllers are used. Frequency deviation (1f) and its derivative (d1f), as illustrated in Fig. 3, are the inputs to the FPI controller. Fuzzification, fuzzy inference system (FIS), and defuzzification make up the fuzzy process. The crisp value is mapped to a fuzzy input value based on the matching membership function as the fuzzification process begins with the crisp input data.

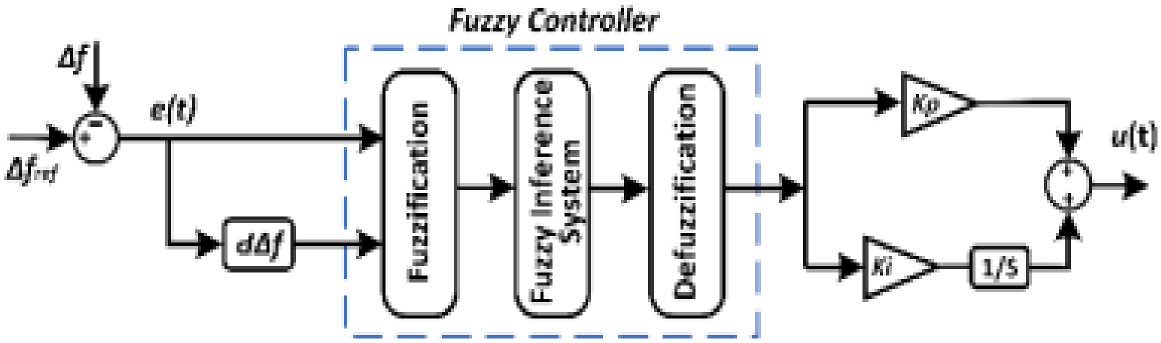

Figure 3 Inputs to the FPI controller

RESULTS AND DISCUSSION

This study seeks to verify the proposed swapping pattern by ensuring it produces the appropriate set of distinct ZSS across all levels. This is then contrasted with PWMs documented in academic sources.

The methodology begins with crafting triangular waveforms, and then pinpointing the intersection points between carrier waves. This subsequently leads to the derivation of ZSS for the chosen carrier switch mode. To underscore the intricacies involved in expanding the SPS-PWM without a predefined scheme, we executed a comprehensive search to find the ideal solution when swapping two pairs of carriers in a 49-level inverter.

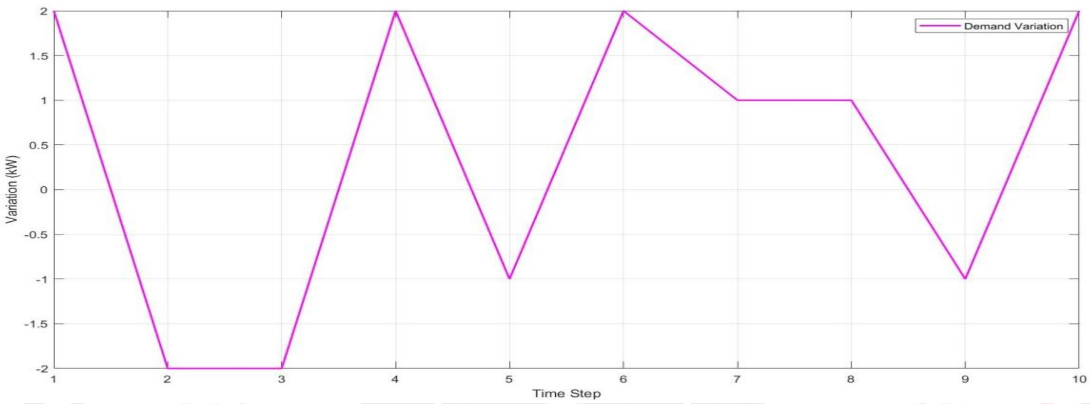

Figure 4: Demand Variation

Figure 4: shows the graph of Demand Variation which is plotted between Variation and Time step showing that time step is fluctuating as increasing of variation and at 1.5 it gradually increases.

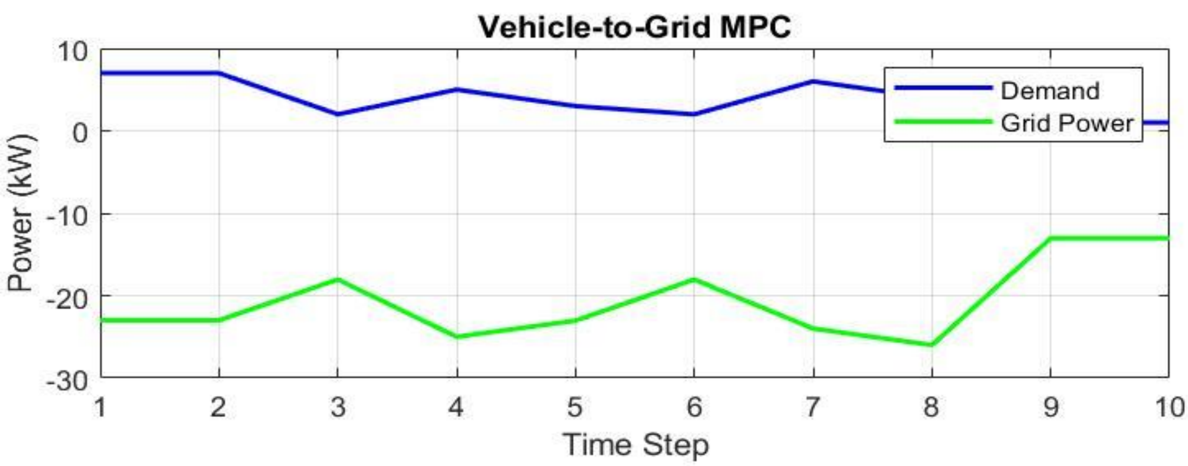

Figure 5: the graph of Grid Demand Vs Power using GWO based PI Controller

Figure 5 shows the graph of Grid Demand Vs Power using GWO based PI Controller which is plotted between Power and Time step showing that time step is fluctuating as increasing of power and at 10 it remains constant.

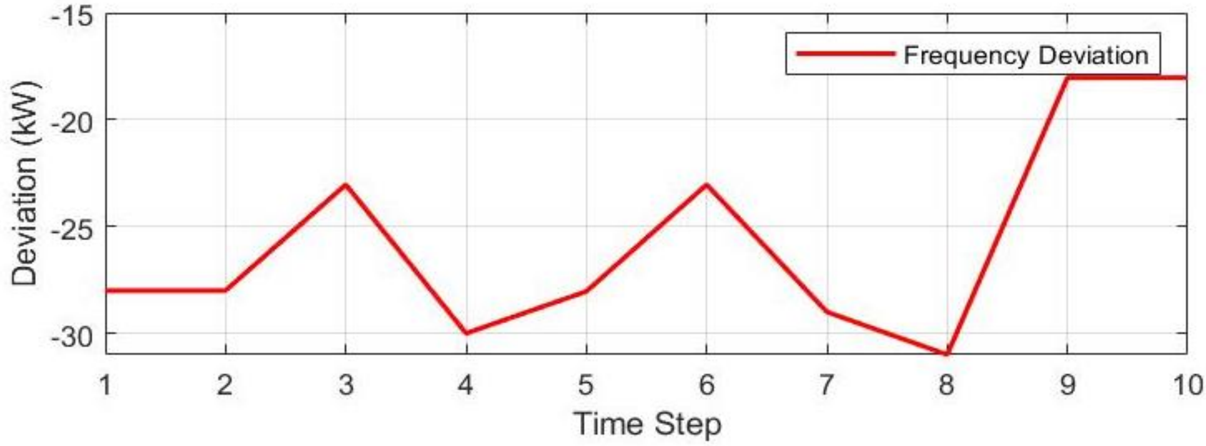

Figure 6 Frequency Deviation for GWO based PI Controller

Figure 6 shows the graph of Frequency Deviation for GWO based PI Controller which is plotted between Deviation and Time step showing that time step is fluctuating between 1 to 8 then gradually increases at 10.

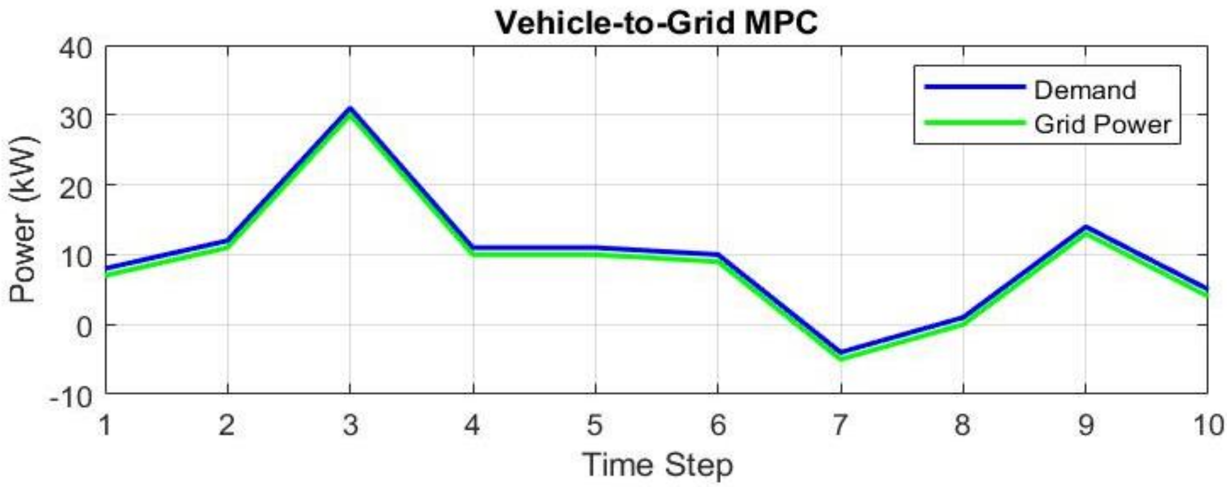

Figure 7: Grid Demand Vs Power using GWO based Fuzzy Controller

Figure 7 shows the graph of Grid Demand Vs Power using GWO based Fuzzy Controller which is plotted between Power and Time step showing that time step and power is fluctuating between 10 to 7 then gradually increases at 9 then comes down at 10.

CONCLUSION

This research focuses on addressing the frequency stability control issue in isolated microgrids (MGs). Various control techniques, including proportional integral (PI), fuzzy logic proportional integral (FPI), and model predictive control (MPC), are employed. The system comprises electric vehicles (EVs), an energy storage system (ESS), a wind turbine, a solar system, and a diesel generator. The controllers are used to regulate the output of the ESS and the EVs' batteries. The impact of load variation and high renewable energy penetration on system frequency is analyzed. The controllers' parameters are optimized using a GWO algorithm. MATLAB/Simulink is used for validation, showing that the proposed control techniques effectively restore frequency deviation and outperform other controllers in terms of efficiency. Future work includes designing a single controller to regulate the state of charge (SOC) of both ESS and EVs and considering the role of converters controlling wind and solar power in the frequency response model.

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