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Two-Stage Robust Optimization for Multiple Microgrids with Varying Loads under Uncertainty Conditions

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Abstract:

The volatility in electricity consumption caused by the growing integration of Electric Vehicles (EV) might significantly impact the reliability of microgrids. Hence, this study aims to decrease the operational expenses of multi-microgrids and enhance the efficiency of solution algorithms for their enhanced electric power distribution. This is achieved by introducing an innovative two-stage robust optimization dispatch system that considers the uncertainties related to loads, renewable energy sources, and electric vehicle consumption. The multi-microgrid layer adjusts the limitations based on the number of EVsadded in real-time and manages various energy units to achieve the minimum operational expenses in the most unfavorable situations. The EVAggregator (EVA) layer ensures minimal power outages and optimal charging operations by regulating charging power while preventing safety breaches. The enhanced uncertainty set is derived from a neural network that undergoes training using a substantial amount of past information, thereby eliminating unrealistic worst-case situations. The suggested method effectively captures the system's features, allowing for the substitution of a considerable amount of past information with system attributeswhen creating the uncertainty set. This approach ensures both high dependability and a substantial decrease in convergence time.

Keywords: Robust Optimization, Microgrids, Uncertainty, Electrical Vehicles.

1. Introduction toMicrogrids and Optimization

Real-world decision-making issues often involve uncertainties and distinctive mathematical programming methods have been established to address these uncertainties. These methods include scenario-based or chance-constrained stochastic initiatives, Robust Optimization (RO), and distributionally robust optimization, designed to accommodate the particular features of different usages [1]. RO aims to find a solution that minimizes risk by carefully analyzing the potential negative impact of all possible outcomes of the unknown variable within an established range of uncertainty. It is particularly appealing when the decision-making needs more information on the probability densities of the unknown variables or when prioritizing the framework's viability over the whole uncertainty set. RO has become increasingly popular in recent centuries due to its significant benefits in modeling capacity, practicality, and mathematical tractability. It has been applied in various fields, such as process organizing, energy system planning and time management, and optimizing networks.The Enhanced Particle Swarm Optimization-driven Intrusion Detection and Secure Routing Algorithm (EPSO-IDSRA) is utilized in this study [2]. In network load , the Enhanced Particle Swarm Optimization (EPSO) method has enabled energy-efficient, secure, and confidence-based routing.

The adoption of microgrids has been growing due to their capacity to incorporate diverse distributed autonomous sources of electricity, such as Wind Turbines (WT), Fuel Cells (FCs), and Energy Sources (ESs), in addition to Renewable Energy Resources (RES) and photovoltaic (PV) energy resources, within a specific area [18]. The growing use of Electric Vehicles (EVs) in recent years has been a significant factor in this pattern, primarily because of the smart and easy power distribution facilitated by the Vehicle-To-Grid(V2G) method [3]. This mode allows for a two-way flow of electricity between EVs and microgrids. Nevertheless, the relationship between EVs and microgrids differs from traditional sent energy sources or electric loading. Many individual EVs in a particular region are connected to a unified Electrical Vehicle Aggregation (EVA) [4]. The EVA's primary goal is to maximize the V2G procedure by controlling EVs' charging and discharging activities. This optimization aims to provide economic benefits to EV users. Hence, the microgrid connectivity attributes of these EVs will be influenced by the unpredictability linked to the actions of individual EV consumers and the activities of intermediate EVAs. The rising number of multi-microgrid networks, especially those with complicated layouts, exacerbates the issue. These systems already need more certainty in demand and the addition of RES. However, the unpredictability of electric power requests caused by the growing use of EVs can significantly impact these multi-microgrid structures' financial viability and stability.

An innovative two-stage robust optimization dispatching system uses the suggested uncertainty set. The robust dispatching model adjusts the limits based on the amount of real-time EV updates to achieve the minimum operational cost of multiple microgrids in the most unfavorable situations. The affordable EVA model has minimal power outages and optimal EV charging operations.

The following sections are organized in the given pattern: section 2 discusses the literature survey about optimization in the EV domain. Section 3 proposes the robust energy optimization of EVs and RES. Section 4 discusses the simulation results of the proposed method in terms of power generation, load, etc. Section 5 concludes the research with the conclusion and findings of the study.

2. Literature Survey and Analysis

Prior research has used several techniques to gather historical EV load information, including mathematical equations, deep learning, and artificial neural networks. Marzbnaiet al. used the Autoregressive Integrating Motion Averaging (ARIMA) approach and the Pattern Sequence-based Foreseeing (PSF) method to predict EV electrical consumption [5]. Dinget al. used two dynamic models to simultaneously predict the sales of plug-in electric vehicles and the daily pattern of recharging load in the United States from 2012 to 2020 [6].

Yumikiet al. devised an innovative and optimal method for regulating the frequency and voltage of V2G operations [7]. This method relies on a group of EVs linked to a dispersed power system via a charging point network. Multiple investigators have determined the probability density function of V2G technology to accurately predict the electricity demand from electric vehicles linked to the power grid. The functionalities of optimization, obfuscationutilities on the Android platform are compared and analysed in this paper [8].

Adaikkappanet al. conducted a study on the multi-uncertainty collecting related to aggregations of EVs, precisely the uncertainty in the collecting findings regarding the State of Charge (SOC) for every EV at the moment of initial relationship [20]. They developed a two-layer Model Predicted Control (MPC) strategy for accurately forecasting the EV-imposing demand of a microgrid. González-González et al. suggested a universal time-varying storage model used in various markets and adaptable to diverse, flexible loads [9].

Model variables that reflect many EVs are easily combined by summing, and load prediction can be performed using autoregressive methods. Haramet al. created an environmental management structure with two main parts [10]. The first part was an ARIMA system to forecast PV generation. The second part was a mixed-integer linear programming structure that efficiently distributed electricity to EVs to minimize charging expenses.

Chaiet al. developed an effective two-stage unpredictable model to address the operational challenges of a microgrid with EVs [11]. The model takes into account the unpredictability associated with EVs. The first stage involves power dealing with the primary grid, while the subsequent phase focuses on optimizing the allocation of microgrid assets. This model is used to inform the decision-making procedure.

Akhgarzarandyet al. aimed to solve the issue of over-conservatism in the RO results achieved when integrating the uncertainties related to EV demands by adding a dispatch spacing factor to control the conservative degree [12]. Zhanget al. defined RO as the problem of finding the shortest route in a probabilistic environment [13]. The goal function of this issue was a combination of the weighted usage of WT and the overall cost of EV recharging.

Wuet al. developed a financially successful microgrid that facilitates trading energy and reserves via energy and resource markets [14]. This grid ensures an appropriate balance between the expenses and advantages of trading and buying energy characteristics. The innovative periodic box ambiguity set restriction was used to include the uncertainties. Kumaret al. introduced a resilient model for enhancing the efficiency of V2G charging and discharging planning [15]. The dispersed RO methodology allowed V2G aggregation to effectively handle operational risks, such as customers' travel requests, even without having complete knowledge about the distribution information.The image classification models developed in this research were compared across five distinct datasets comprising different quantities of data [17]. In achieving this objective, four discrete pre-trained models—VGG16, InceptionV3, MobileNet, and DenseNet—are utilized. In addition, a novel model was proposed, which was trained using the provided datasets.A novel hierarchical non-linear machine learning technique is presented in this article [19]. It is proposed to utilize multivariate adaptive regression spline with genetic algorithm in order to manage the energy demand of smart grids.His research examines the feasibility of identifying a candidate for a heavy load solver through a heuristic approach involving the integration of multiple crossover methodologies into an artificial bee colony (ABC) [21].

3. Proposed Robust Optimisation Algorithm for Microgrids

The focus of this work is on grid-connected microgrids. The residual capacity of the microgrid is exchanged with the primary grid, and any excess power from the microgrid can also be bought from the primary grid. The microgrid examined in this research encompasses conventional dispersed energy resources, sustainable dispersed power sources, batteries, and loads. Traditionalscattered power supplies include miniature gas turbines, whereas renewable distributed energy sources include wind turbines and photovoltaics.

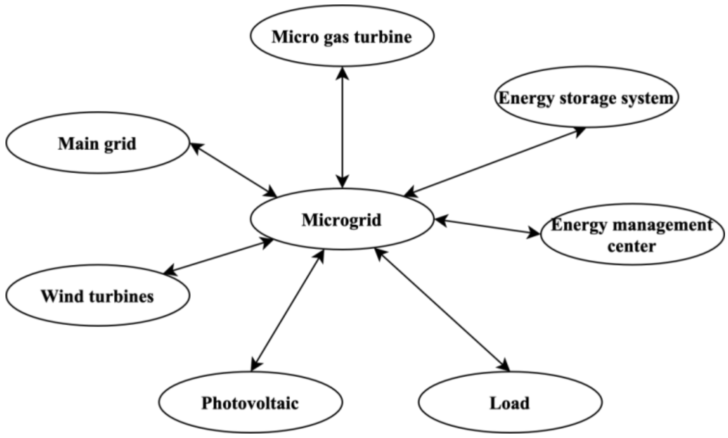

Figure 1. Grid-connected microgrid structure model

Figure 1 depicts a schematic representation of the microgrid configuration. The energy monitoring center and the microgrid alone engage in data exchange. The energy monitoring center uses previous information on power production from dispersed RES and historical use data of the demand to anticipate the future generation from the RES and the need for electricity during the following duration. The energy managing center does RO computations using predictions to determine the ideal dispatching strategy for the microgrid. This scheme is designed to minimize the operating expenses of the microgrid. According to this system, the power managing center then carries out the optimum forecasting of the microgrid.

3.1 Robust characterization of uncertain variables

The uncertainty variables include the production of RES and the load demand. The research proposes a strong alternative description for renewable distributed power, which involves specifying photovoltaic energy output and wind power generating results.

3.1.1 Robust representation of PV output

The solar irradiance for a PV unit at point p and time duration t is modeled using a Beta dispersion function, characterized by its form and rate characteristics as defined in Equation (1).

$$P_{x.t}^{PV} = \beta\left(\alpha_{x,t}, \beta_{x,t}\right) \quad (1)$$

To rectify the inaccuracy in the probability approach, it is necessary to include robust adjustment variables $(\alpha_{x,t}, \beta_{x,t})$ to change the system. The built photovoltaic power supply is represented robustly in Equation (2), and the predicted PV power is expressed in Equation (3).

$$P_{x.t}^{PV} = CDF_{x.t}^{-1}\left(\hat{P}_{x.t}^{PV} - \rho\right) \quad (2)$$

$$\hat{P}_{x.t}^{PV} = \int_{-\infty}^{E_{PV,t}} P_{x.t}^{PV} dt \quad (3)$$

The predicted power is $\hat{P}^{PV}_{x.t}$, and the percentage of $E_{PV,t}$is determined based on the forecasted performance of photovoltaic systems.

3.1.2 Robust representation of WT output

The wind speeds for a wind turbine unit at location u and time duration t are supposed to conform to a Weibull dispersion function, characterized by its form and scale variables as defined in Equation (4).

$$P^{WT}_{w,t} = Weibul\left(C_{w,t}, \delta_{w,t}\right) \quad (4)$$

The robust depiction of WT ($\delta_{w,t}$), comparable to the robust corresponding depiction ($C_{w,t}$) of solar power production. The power of WT is expressed in Equation (5) and the predicted power is WT is expressed in Equation (6).

$$P^{WT}_{x.t} = CDF^{-1}_{x.t}\left(\hat{P}^{WT}_{x.t} - \rho\right) \quad (5)$$

$$\hat{P}^{WT}_{x.t} = \int_{-\infty}^{E_{WT,t}} P^{WT}_{x.t}\,dt \quad (6)$$

The prediction variable is$\hat{P}^{WT}_{x.t}$ for WT. The calculation of $E_{WT,t}$is based on the expected value of wind turbine production.

3.1.3 Robust representation of load

The active energy and reactive energy of the load request at bus x and interval t are taken to conform to a bivariate regular distributed function, as described in Equations (7) and (8).

$$P^{D}_{x,t}, Q^{D}_{x,t} = N_w\left(\alpha, p_{x,t}\right) \quad (7)$$

$$\alpha = \left[\mu^{P}_{x,t}, \sigma^{P}_{x,t}, \mu^{Q}_{x,t}, \sigma^{Q}_{x,t}\right] \quad (8)$$

The load demand ($P^{D}_{x,t}, Q^{D}_{x,t}$) robust comparable depiction ($\mu^{P}_{x,t}, \mu^{Q}_{x,t}$) must be modified using robust adjusting variables ($\sigma^{P}_{x,t}, \sigma^{Q}_{x,t}$). The load requirement is represented robustly in Equation (9).

$$P^{D}_{x,t}, Q^{D}_{x,t} = CDF^{-1}_{x.t}\left(\hat{P}^{D}_{x.t} + \rho, \hat{Q}^{D}_{x.t} + \rho\right) \quad (9)$$

3.1.4 Robust adjustment variables

The calculation method for the resilient adjusting variables discussed above appears in Equation (10):

$$\delta = A \times \beta \quad (10)$$

The parameter β has a value ranging between 0 and 1, exclusive. The computation method for variable A is presented in Equations (11) and (12):

$$A = \min\{P, 1 - P\} \quad (11)$$

$$P = \max\left\{P^{D}_{x,t}, Q^{D}_{x,t}, P^{PV}_{x,t}, P^{WT}_{x,t}\right\} \quad (12)$$

The power and quality demand are $P^{D}_{x,t}, Q^{D}_{x,t}$, the PV and WT generated power are denoted $P^{PV}_{x,t}, P^{WT}_{x,t}$.

3.2 Optimal scheduling

The technique addresses the resilient dispatch issue by iteratively solving two Major Problems (MPs) and Sub-Problems (SPs). The MP is utilized to acquire a precise uncertainty situation, while the dualized SP is employed to ascertain the presence of more unfavorable situations inside the collection of uncertain situations.

3.2.1 Cutting plane robust dispatchingmodel

The technique applies the MP to resolve the robust dispatch system under perfect conditions without any ambiguity. The dualized SP is employed to verify when the solution achieved is resilient in the worst-case situation. McCormick masks are often utilized to address the issue of linking uncertainty parameters in the dual transformation procedure of the dualized SP. The answer obtained from the SP is submitted as input to the MP, and this iteration process is continued.

The dispatch method relying on the usual tangential plane technique is defined as a two-stage RO approach using Equations (13) to (15).

$$MP: \min\{Ai\} + \varphi \tag{13}$$

$$\delta = \begin{cases} \varphi > Bj, Fi > f, Gj > g \\ Uj + Vv = k, Ci + dj > d \end{cases} \tag{14}$$

$$\varphi = \{v | \hat{v}_x - \alpha_x \beta_x < \hat{v}_x + \alpha_x \beta_x, \textstyle\sum_{x=0}^{N} \alpha_x < \tau\} \tag{15}$$

$\alpha_x$denotes the ratio of the most significant offset β_x, with α_x being a number between 0 and 1. $\hat{v}_x$indicates the anticipated value of the x-th uncertainty parameter. Likewise, the SP is defined in the same manner using Equations (16) and (17).

$$SP: \max\{g^T c\} - (Ci - l)^T \alpha - (Vv - k)^T \gamma \tag{16}$$

$$B^T - \{G^T c + D^T \alpha + U^T \gamma\} = 0 \tag{17}$$

Utilizing McCormick masks transforms the SP into a conventional linear issue.

3.2.2 Enhanced robust dispatchingmodel

The conventional model relies on a predetermined basic geometric structure. This structure considers all uncertainties in the most unfavorable situation, along with a particular structure for creating an organizing plan. The standard data-driven modelutilizes all previous data from a specific setting to identify the most unfavorable scenarios. Unlike dealing with continuum uncertain characteristics, the current study also encompasses binary uncertainties. This binary unpredictability pertains to the count of suddenly detached EVs, variables with integer values. These variables could introduce interdependence in the dualization procedure of the SPs. The data-driven approach avoids laborious processing procedures by utilizing particular situations from the indirect setting set as the initial point in the two-layer robust dispatch procedure. Despite a rise in analyzing complexities, this is a significant advantage of the proposed data-driven ambiguity set.

An additional strategy to enhance the computational effectiveness of the two-stageRO dispatching technique is using a sub-uncertainty group Λ. In this set, just one situation is used in the initial iteration. The binary parameter derived from resolving the MP is sent into the SP, providing the worst-case possibilities.

3.2.3 Optimal scheduling of the EVA layer

To achieve the desired divergence of the uncontrolled parameter from the perfect G_x, it considers the charging power and SOC of an individual EV as separate factors. Using these variables, the systems create the transmitted energy matrix $K_x$and SOC matrix L_x.The approach of multi-objective planning is used, using deconstruction and weighing techniques. It derives the charge index scalar $P_x$and SOC series $S_x$of the ideal setting. Equation (18) showsG_x.

$$G_x = \sum_{t=0}^{T} \sum_{x=0}^{N} \sum_{y=0}^{N} \frac{(P_{EV})^2}{2P_x} + \frac{(S_{EV} - S_{EV}(x))^2}{2S_x} \tag{18}$$

The combined resolution of linear programming determines the last scheme's reasonableness.

1. Acquire past information to train the Neural Network and then use it to determine the features of situations, identify the connection between various types of uncertainty, and construct the correlation architecture.

2. Utilize the trained Neural Network to forecast likely situations in the following scheduling duration, then employ these situations to construct the polyhedral uncertainty collection.

3. Calculate the variable τ_x based on the current total SOC and the number of EVs linked to the microgrids while considering the limitations.

4. Begin the framework by assigning the higher limits Ψ^* as positive infinity, the smaller limits $\widehat{M}$as negative infinity, and the iterative index x as 0.

5. Use the MP technique to address the minimum cost in the most unfavorable situation of the sub-uncertainty group Λ, determiningM_x^* and I_x^*.

6. Transfer the value of $I_x^*$to the SP.

7. The SP algorithm seeks to identify a collection of uncertainty possibilities, denoted as Ψ_x^*inside the enhanced uncertainty set. If the absolute difference between $\Psi_x^*$and $M_x^*$is less than or equal to ε, go to step (8). Alternatively, include the scene in Λ, increment the value of x by 1, and go to step (5).

8. Utilize the MP algorithm to derive the ideal programming plan Ψ_{x+1}^* in the most dire case of Λ. If the absolute difference between the complex conjugates of Ψ_{x+1}^* and Ψ_x^* is less than or equal to ε, proceed to step (9); alternatively, go back to step (6)

9. Determine the total power consumption (P_{EV}) and total energy consumption (S_{EV}) by considering the charging schedule of each distinct EV at the lowest EVA level. If it is not possible to satisfy the safety restrictions, then adjust $\tau_i^{x+1} = \tau_i^x \exp(1 - G_x)$, and go back to step (4).

4. Simulation Analysis and Outcomes

The multi-microgrid evaluation system comprises four microgrids and their corresponding line connections. During the models, itconsiders a maximum variation in RES production of ±25% from its usual value. The most significant variations in energy demands are ±10% from their average values. Microgrid (MG1) is characterized as a business region with high activity levels. The longest time for EVs to connect in EVA1 is 5 hours in MG2.

MG3 is designated as a residential neighborhood, and the longest time for EVs to be connected in EVA2 is 7 hours in MG4. Each of the four microgrids implements a three-stage power pricing strategy. This policy applies low electricity rates during late night and dawn, ordinary electricity rates throughout the morning and this afternoon, and high energy prices at midday and evening.The numerical calculations were performed on a computer with an8-core 2.4 GHz CPU and 8 GB of RAM running the Windows 8 operating system. The YALMIP toolkit in MATLAB was used to create multilevel, two-stageRO dispatching systems [16]. The alternative models were used in four distinct cases, and their outcomes were contrasted to determine the specific advantages of the suggested strategy.

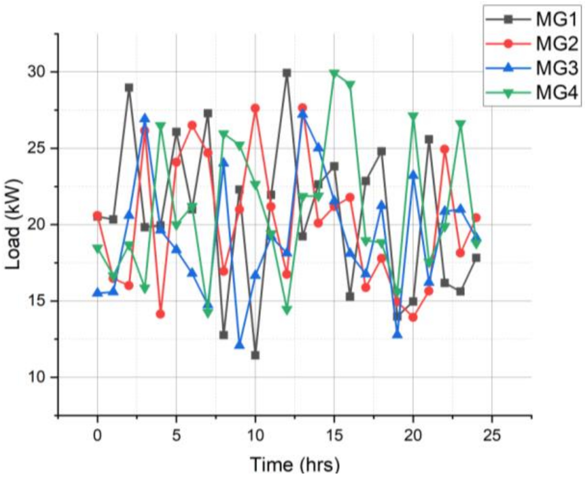

Figure 2. Load analysis of different MGs

Figure 2 depicts the varying load profiles of Microgrids (MG1, MG2, MG3, MG4) across a 24-hour duration. The average findings reveal diverse load patterns across the microgrids, with MG2 regularly demonstrating larger loads. The fluctuation in load highlights the need for customized approaches in Microgrid functioning, which significantly affects the general efficiency and results of the Microgrid system.

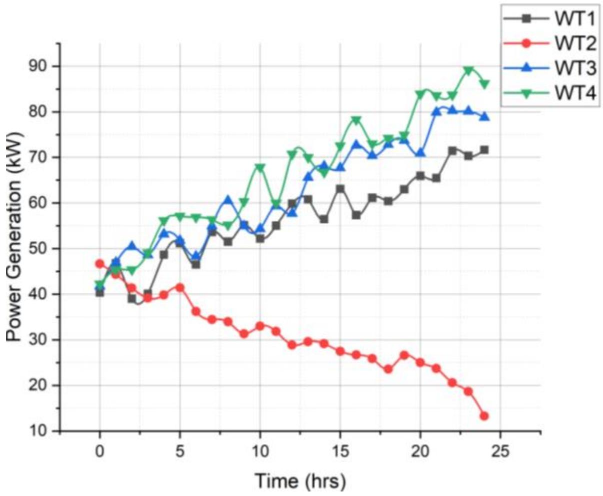

Figure 3. Power generation analysis of different WTs

Figure 3 illustrates the power production patterns of Wind Turbines (WT1, WT2, WT3, WT4) across 24 hours. WT4 consistently exhibits superior power production, while WT2 has somewhat worse performance. The significance of these variances highlights the need for efficient management techniques, which influence the overall result and effectiveness of the Wind Turbine structure in the power production.

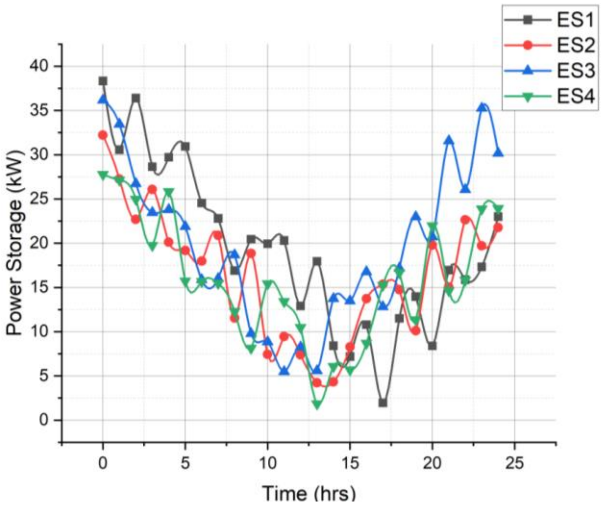

Figure 4. Power stage analysis of different ESs

Figure 4 depicts the fluctuations in power storage for Energy Storage systems (ES1, ES2, ES3, ES4) across 24 hours. ES3 regularly has superior power storage capabilities compared to other models, whereas ES2 shows comparatively poorer performance. The significance of these differences underscores the pivotal importance of efficient energy storage management, which directly affects the energy storage system's outcome and dependability within the power distribution and storage framework.

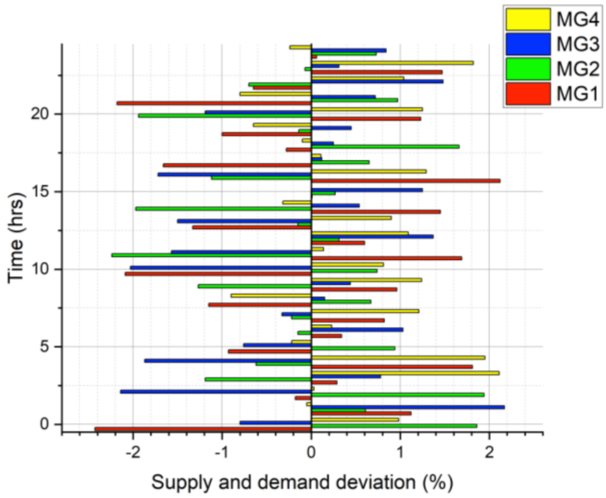

Figure 5. Supply and demand deviation analysis

Figure 5 displays the percentage differences between the supply and demand of Microgrids (MG1, MG2, MG3, MG4) throughout 24 hours. MG2 often has minor variance, but MG1 and MG3 have balanced variability. The significance of these variances highlights the need for accurate control and management measures to guarantee effective alignment of supply and demand, hence affecting the overall dependability and consistency of the Microgrid system.

The optimization findings indicate different load patterns in Microgrids (MG1-MG4) with variable average deviations. MG2 has the lowest deviation at 0.05%, while MG1 and MG3 have balanced variations about 0.42%. Among the Wind Turbines (WT1-WT4), WT4 constantly surpasses the others by generating an average of 69.71 kW. This highlights the effectiveness of its energy-producing tactics. The dynamics of Energy Storage (ES1-ES4) show that ES3 consistently maintains the most significant average storage capacity at 21.84 kW. This highlights the critical function of ES3 in guaranteeing dependable power distribution and reducing variations.

5. Conclusion and Findings

This study aimed to enhance the cost-effectiveness and safety of multi-microgrid structures and increase the efficiency of algorithmic approaches in dealing with uncertainties related to loads, energy from renewable sources, and electric vehicle use. The achievement was made by introducing an innovative two-stage RO dispatching approach, including an upper-level RO dispatching approach for the multi-microgrid network and a lower-level EV aggregation forecasting system. The operational limitations of the higher level are adjusted based on the real-time number of additions and the current charge level of every EVto achieve the lowest running cost in the most unfavorable situations. The system uses neural networks to analyze the pre-selected past information of the closely connected and unpredictable group to implement the effective planning method in the higher layer. The resulting many scenarios with various periods provide an enhanced collection of uncertain characteristics. The bottom level of the system is built upon the innovative grid-connected design for electrically powered automobiles. To ensure the safe recharging for every EV, a multi-objective optimizing system is used to construct charging strategies.This approach ensures both high dependability and a substantial decrease in convergence time.

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