

Optimizing Multi-Microgrid Operations: A Compromise Approach Incorporating Loss Considerations and Renewable Energy Uncertainty

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ABSTRACT: The significant integration of variable renewable energy sources, along with the uncertainties in their generation, presents a substantial challenge for the distribution system operator. Microgrids, recognized as intelligent grid systems, offer a promising solution for the efficient integration of local renewable energy resources. However, the intermittent nature of renewable energy introduces operational complexities and additional costs associated with maintaining stable performance within the microgrid's energy management system. The presence of multiple microgrids facilitates the creation of a flexible and diversified energy market structure. This paper investigates the impact of losses on microgrid expenses through the analysis of various scenarios. A compromise model objective is proposed, focusing on the minimization of microgrid costs. To address the uncertainties associated with variable renewable energy sources and their impact on system costs, distributed energy resource schedules, and the overall energy market, we propose a new data-driven probabilistic efficient point method. This method calculates the optimal generation from sustainable energy at various risk levels, which can then be integrated into a suggested transactive day-ahead market model. Simulation results confirm that the proposed compromise strategy is feasible, with system cost nearly matching the minimum achievable. Specifically, during peak demand periods, the compromise scenario yields a 3% reduction compared to the actual system cost. Likewise, system losses, which reach their maximum during high-demand intervals, are reduced by 2.5% under the compromise-based solution relative to the actual system. These outcomes confirm the effectiveness of the proposed approach in simultaneously achieving economic efficiency and technical reliability.

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1- Introduction

1- 1- Motivation and approach

In contemporary power grids, the proliferation of distributed energy resources (DERs), including solar and wind power, battery storage systems, and controllable generators, necessitates the implementation of effective integration strategies. Microgrids emerge as a promising solution for optimizing the utilization of DERs within local power grids [1,2,3,4]. The integration of small-scale, modular distributed generation units and energy storage systems into low- and medium-voltage distribution networks has given rise to a new paradigm in power systems, referred to as microgrids (MGs). From the perspective of the utility operator, a microgrid can be regarded as a controllable and flexible load whose power consumption can be dynamically adjusted according to operational conditions. Specifically, the load may remain constant under normal circumstances, increase during off-peak periods when electricity costs are lower, or be curtailed to minimal or even zero levels during

network stress or critical events. Microgrids can be deployed across diverse environments, including commercial centers, industrial parks, and university campuses. A defining feature of microgrids is the proximity of distributed generation resources to the end-users, enabling both grid-connected operation and autonomous islanded mode, thereby enhancing operational flexibility, reliability, and resilience of the local power system. Figure 1 illustrates a representative microgrid configuration [5,6]. While microgrids offer several advantages, including enhanced grid reliability, increased flexibility for future grid expansions, and reduced transmission losses, operating as standalone entities can expose them to vulnerabilities. Single microgrids may be susceptible to interference and can experience operational breakdowns due to a single fault, hindering their intended efficiency [3,7]. To address the challenges associated with standalone microgrids, the concept of Multi-Microgrids (MMGs) has been introduced, wherein multiple microgrids are interconnected in terms of power and energy exchange. Figure 2 illustrates a representative MMGs configuration. MMGs offer enhanced efficiency, superior techno-economic

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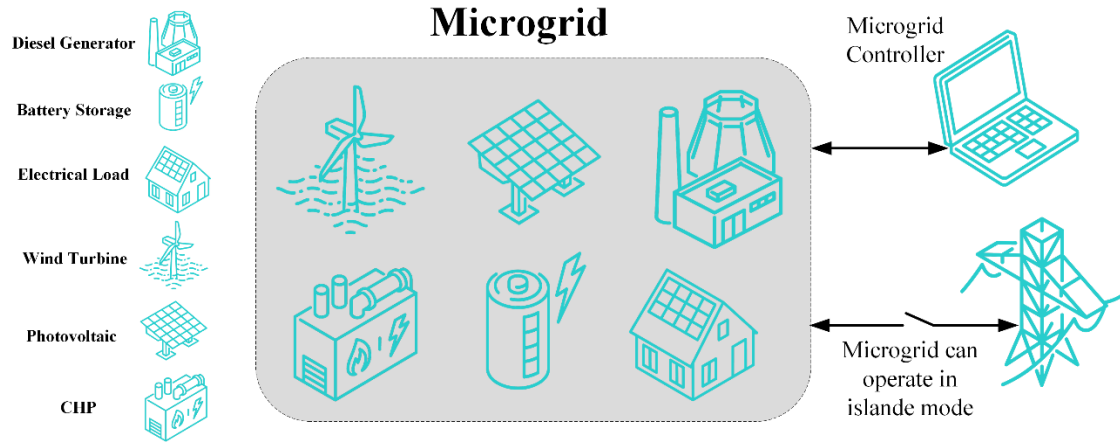


Fig. 1. Schematic of a microgrid

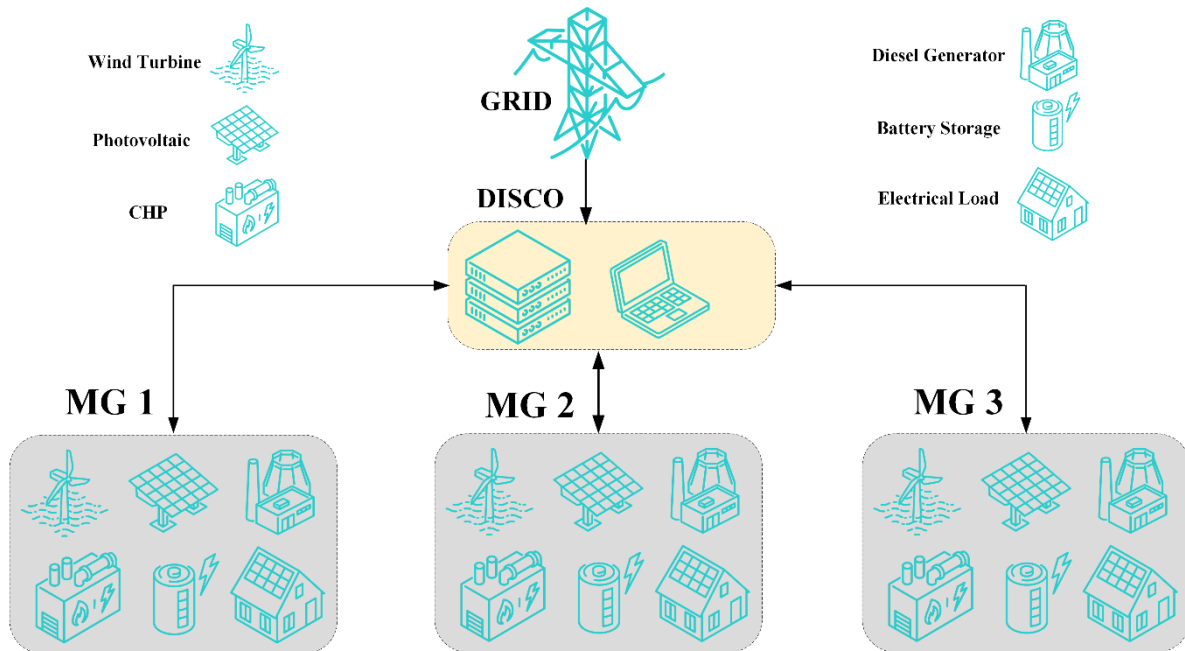


Fig. 2. Schematic of a multi-microgrid

advantages, and greater adaptability and resilience compared to individual microgrids. Microgrid operation modes can be classified into grid-connected mode and islanded mode, contingent upon their interaction with the distribution networks [2,7]. Financial incentives offered by Distribution System Operators (DISCOs) serve as an effective mechanism to encourage the strategic deployment and utilization of Distributed Generators (DGs). Pricing methodologies, particularly Locational Marginal Pricing (LMP), play a pivotal role in this incentive-based approach. While LMP offers a valuable tool for achieving short-term efficiency by calculating marginal prices at network nodes, including those with DGs, its implementation in distribution networks and microgrids can lead to fluctuations in generation values and parameters, potentially impacting their economic operation.

DISCOs can leverage LMP as a strategic tool for controlling and operating networks to align with their objectives [1,8]. To address the uncertainties inherent in the increasing integration of variable renewable energy (VRE) production, we propose a novel data-driven probabilistic efficient point (PEP) method. This approach leverages historical data to calculate expected VRE generation values at various confidence levels, which are subsequently incorporated into the distribution location marginal pricing (DLMP)-based day-ahead market (DAM) model. The PEP method empowers the Distribution Network Operator (DNO) with Increased adaptability in managing the uncertainties associated with VRE production. Moreover, this paper presents valuable insights into the significance of reactive power pricing and provides a detailed analysis of the Beneficial and detrimental elements of DLMP under varying levels of VRE implementation and reliability.

1- 2- literature review and contributions

This paper proposes a frequency-based energy management system (FEMS) for the autonomous operation of a residential MG, incorporating a lithium-ion battery energy storage system (LIBESS) and DGs [9]. To optimize the utilization of renewable energy resources and address energy distribution challenges within islanded MMGs, a sequential algorithm combining symbiotic search (SOS) and a distributed robust algorithm is suggested [2,10]. This research focuses on DC standalone multi-microgrid systems, emphasizing their inherent adaptability, resilience, and operational effectiveness in managing fluctuating, variable, and unpredictable generation shortfalls [11]. Paper [12] presents a resilient optimization framework for the collaborative operation of microgrid-centralized energy storage systems (MG-CES), incorporating distributed generation amidst uncertainty. The proposed model adopts a two-stage, four-layer structure, referred to as “min-min-max-min.” In [13,14], the focus is on the distributed energy management of MMGs to achieve energy coordination, incorporating precise modeling of demand-side resources. The primary objectives include minimizing carbon emissions and fostering self-organization within each MG. This paper proposes a convex optimization framework for an energy management system, integrating interactions within a local energy marketplace across three asymmetrical microgrids. The goal is to either minimize consumer expenses or maximize supplier profits [1]. This study identifies and examines clustered or synchronized renewable energy-driven microgrids capable of providing support services, participating in market activities, and facilitating inter-microgrid communication. These attributes contribute to enhanced grid flexibility and reliability [15]. This paper proposes an optimal multi-energy microgrid configuration within the electricity market. The objectives of the proposed framework encompass hierarchical cooperative optimization of the microgrid system, dynamic pricing based on supply-demand dynamics, cost minimization, penalty-based enforcement of consistency, and robust demand response [16]. Furthermore, this paper introduces an economic strategy aimed at reducing line currents to mitigate strain on line capacity, minimize losses, and enhance overall network reliability within microgrids and dynamic distribution networks, including DG [8]. This research introduces Local Energy and Reserve Markets (LERMs), enabling Microgrid Managers (MGMs) to effectively meet their energy and storage needs through strategic resource planning and competition with other microgrids [17]. [18] investigates a market-oriented pool approach for a MG to facilitate efficient electricity trading within the distribution electricity market (DEM). A distributed robust model predictive control (DRMPC) energy management strategy is proposed for islanded multi-microgrids to mitigate the adverse effects of uncertain renewable energy output [19]. In ref. [20] introduces a flexible two-stage joint planning model for MMGs based on non-cooperative game theory for electricity price fluctuations and seeks to address the joint profit allocation problem using a generalized Nash equilibrium for energy Uses. [21]

presents a comprehensive electricity market model for a smart microgrid, incorporating a stochastic allocation of distributed resources and an optimal demand response analysis. This model prioritizes environmental sustainability through the utilization of renewable energy sources (RES), enhances system reliability by incorporating conventional generators, and emphasizes economic efficiency by flattening demand curves. To facilitate efficient electricity trading among multiple grid-connected microgrids and their participation in ancillary services markets, this paper proposes a real-time market trading mechanism [3,22,23]. Reference [24] introduces a methodology for neighboring microgrids within a distribution network to collaborate and establish a multi-microgrid (multi-MG) configuration, integrating a cloud energy storage system (CES). This initiative aims to enhance profitability and reliability. The article commences by providing an overview of existing market structures at the distribution level and their initial deployment. Subsequently, it delves into a comprehensive examination of the application of distribution location marginal pricing (DLMP) for managing and planning DERs and distribution system operators (DSOs) [25]. This paper introduces a novel contract theory framework designed to address the complexities inherent in formulating efficient contracts for electricity suppliers (ESs). A dynamic pricing model is proposed to incentivize ESs to meet both base load and peak load demands, tailored to their respective classifications [26]. This paper introduces a two-stage stochastic collaborative approach for wind power plants (WPPs) and pumped storage power plants (PSPs) operating within a microgrid. The proposed framework is designed to effectively address the challenges posed by uncertainty constraints and associated penalties [27]. [28] introduces a day-ahead scheduling method for multi-carrier microgrids (MCMGs) that integrate renewable generators and combined heat and power (CHP) units. This method employs a mixed-integer linear programming (MILP) model to optimize scheduling decisions. To address the uncertainties associated with renewable energy, the study incorporates information gap decision theory (IGDT) and a scenario-based stochastic approach. Studies have shown that community-based and game-theoretic approaches can significantly reduce operational costs while enhancing system efficiency, whereas methods such as alternating coefficient orientation provide an optimal trade-off between privacy, performance, and energy utilization [29]. Hybrid optimization techniques, including QI-NLS-G2O combined with GRZPNet, have demonstrated improved load forecasting accuracy and up to 20% enhancement in system efficiency in multi-source microgrids [30]. Multi-objective algorithms, such as NSGA-II-MC, have been employed to manage resilient microgrids, achieving reductions in costs and grid dependency alongside a 49.7% improvement in the Hypervolume metric for large-scale scenarios [31]. Optimal energy management strategies for multi-energy MMG networks have also been proposed, enabling microgrid autonomy, efficient resource allocation, and reductions in carbon emissions by 37.5% and operational costs by 12% [32]. Robust controllers designed using MOPSO

and MOGA have proven effective in islanded microgrids, enhancing system stability, transient response, and tolerance to uncertainties in renewable generation and variable loads [33]. Real-time optimal strategies incorporating energy storage participation have further increased renewable energy utilization while improving system reliability and flexibility [34]. Moreover, the integration of EVs into multi-source microgrids has been shown to significantly influence optimal performance and energy management policies due to uncertainties in charging times and connection locations [35]. Collaborative scheduling models employing improved Genetic Algorithms and Particle Swarm Optimization have facilitated higher renewable energy accessibility, reduced operational costs, and ensured system stability [36]. Finally, hybrid PV-wind-fuel cell MMG systems optimized via the Grey Wolf Optimizer, as well as two-stage robust models for islanded microgrids, have demonstrated cost reduction, enhanced accuracy, faster convergence, and minimized investment and operational costs under renewable energy uncertainties [37,38]. Furthermore, a brief overview of recent research details on techno-economic analysis of MMGs is given in Table 1.

This paper provides a comprehensive analysis of microgrid optimization, encompassing critical aspects such as economic load dispatch, transmission loss minimization, and the associated economic considerations of system costs. To address the inherent uncertainties stemming from the intermittent nature of renewable energy sources, the Probabilistic Efficient Point (PEP) method is employed. Unlike conventional approaches that rely on complex probabilistic distribution functions, PEP enables the representation of uncertainties using only historical and synthetic data, thereby enhancing modeling accuracy while reducing computational complexity.

From a strategic perspective, the study focuses on the development of a compromise-based objective function that simultaneously optimizes both economic costs and network losses within an integrated framework. This dual-focus approach not only improves decision-making processes in the operation and planning of microgrids but also provides a balance between technical performance and economic efficiency. The conceptual findings highlight the inherent trade-off between cost and losses: minimizing losses often results in increased costs, and vice versa. Consequently, identifying the optimal equilibrium between these two conflicting objectives remains a fundamental challenge in power system optimization. The proposed framework seeks to establish such a balance, thereby offering deeper insights into the techno-economic modeling of microgrids.

The key contributions of this research are summarized as follows:

- Integration of energy management with Economic Load Dispatch (ELD) in a multi-microgrid framework, enabling the simultaneous enhancement of both economic and technical performance of the system.
- Reformulation of ELD considering losses, which are often

neglected in prior studies, thereby ensuring more realistic and practically applicable results.

- Development of a novel compromise-based objective function to establish an effective trade-off between total system cost and losses, allowing for a simultaneous reduction in both indices.
- Formulation of the optimization problem as a Mixed-Integer Linear Programming (MILP) model, ensuring high accuracy, computational efficiency, and suitability for real-world energy market applications.
- To address the inherent uncertainties in variable renewable energy (VRE) generation, a novel data-driven mixed-integer linear programming (MILP) approach was introduced in this paper. Leveraging an extensive dataset of historical VRE generation data, this method effectively solved probabilistic efficient points (PEPs) without relying on any prescribed probability distribution function. Analogous to probabilistic optimization approaches with chance constraints, the PEP method empowered distribution system operators (DSOs) with enhanced flexibility in managing the uncertainties associated with VRE production.

The paper's subsequent sections are structured as follows: Section 2 presents the underlying modeling and mathematical formulation. Section 3 delves into the probabilistic efficient point (PEP) method. Section 4 conducts a comprehensive analysis of the impact of each variable on the desired outcomes. Finally, Section 5 provides a comprehensive summary and conclusion.

2- Modeling and Mathematical Formulation

2- 1- Proposed model MMG

The proposed MMG system is depicted in Fig. 3. Under normal operating conditions, the MMG operates in grid-connected mode. However, all MGs possess the capability to island from the upstream grid at Bus 1, facilitating power exchange among individual MGs. Each MG comprises a diverse mix of conventional and renewable energy resources, mirroring the composition of real-world MMGs. Additionally, these MMGs incorporate storage facilities and local control centers, thereby encompassing the essential infrastructure elements of a practical MMG.

The primary objective of this research is to evaluate the efficacy of the proposed energy market approach within the context of islanded MG operation. Furthermore, Table II provides detailed information regarding the cost and capacity limitations of the individual generators. The identification of optimal operating points for these generators constitutes a key research goal. Figure 4 illustrates the 24-hour system demand profile.

2- 2- Problem formulation

In this paper, an optimization model for the optimal distribution of electricity generation in energy systems is presented. The model is presented in order to minimize the power generation cost and transmission losses, taking into account the load requirements and uncertainty of VRE and

Table 1. A brief overview of recent research in the field of Techno-economic analysis MMG

Ref.	Energy sources used	Main research focus	Main objectives	Optimization method and algorithm	Innovation and differentiation	Research limitations/gaps
[7]	PV ,WT , CCGT	Improving technical and economic conditions	Reduce losses, improve voltage	Cooperative Game Theory	Application of repetitive games in a microgrid	Lack of focus on uncertainty
[8]	PV ,WT , CG, BESS,	Two-level scheduling with carbon markets	Cost and pollutants	Bi-level optimization	Combining the carbon market with multiple island microgrids	Failure to check storage resources
[29]	PV ,WT , BESS ,EV	Multi-microgrid energy management with a focus on EV and BESS	Cost reduction and courier	Multiple comparison algorithms	EV integration in a multi-microgrid management framework	Lack of focus on network losses
[30]	PV ,WT , BESS	Multi-energy management with RES uncertainty	Improve reliability and cost	Hybrid method (definite + probabilistic)	Using a hybrid model for RES	Failure to consider multi-microgrid interaction
[31]	PV, WT, BESS ,CG	Resilience and multi-stage constraint management	Sustainability and cost reduction	Multi-stage MOO	Considering multi-stage constraints for resilience	Failure to consider multi-microgrid cooperation
[32]	PV ,WT , CHP, Boiler, Heat pump	Cost and emissions optimization	Cost and emission reduction	Mountain Gazelle Optimizer (MGO)	New algorithm inspired by nature	No comparison with methods with losses
[33]	CG ,WT, FC	Frequency control in isolated microgrids	Frequency control in isolated microgrids	Hybrid MOO + μ -synthesis	Combining robust control with optimization	Focus on control → not energy management
[34]	PV ,BESS	Real-time control and guidance	Improve real-time response	Predictive storage model	Collaboration between storage providers	Lack of economic cost analysis
[35]	PV ,WT , EV ,BESS	Optimal operation with EV uncertainty	EV Uncertainty Management	Stochastic optimization	EV Uncertainty Modeling	Lack of focus on network losses
[36]	PV ,CHP , BESS	Island design and operation with DRO	Managing uncertainty and sustainability	Distributionally Robust Optimization	Applying DRO to Isolated Microgrid	Failure to consider multi-microgrid interaction
This study	PV ,WT , BESS , CHP, CG	Optimization of multi-microgrid operation by simultaneously considering losses, costs, and uncertainty of renewable resources	Reducing costs and losses, managing uncertainty	Compromise programming + Uncertainty modeling	Combining loss criteria with uncertainty modeling in a compromise framework	Need for broader comparison with new algorithms and more sensitivity analysis.

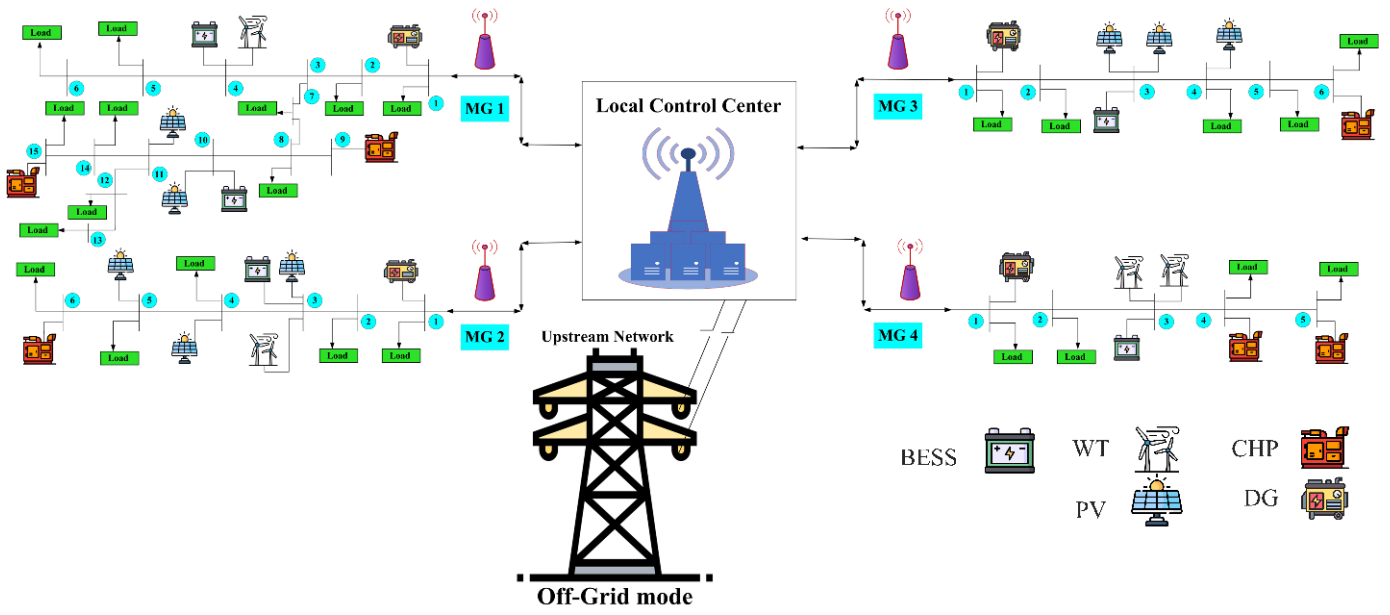


Fig. 3. Schematic of proposed model

Table 2. Cost coefficients and capacity constraints on MGs

Unit	$P_{\max}(\text{MW})$	$P_{\min}(\text{MW})$	Cost Coefficients		
			a_i	b_i	c_i
MG 1	600	150	0.003	2.45	105.0
MG 2	500	100	0.005	3.51	44.4
MG 3	300	50	0.006	3.89	40.6
MG 4	300	50	0.004	2.78	66.9

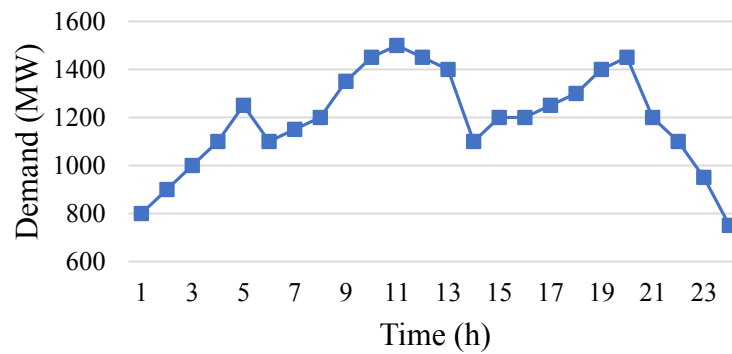


Fig. 4. System demand profile in 24 hours

power plant constraints in MMGs. The following parts of this section provide a meticulous and detailed exposition of the model's equations. Eq. (1) formally defines the total cost of electricity generation, one of the primary objective functions.

$$\text{Minimize : cost}_{MMG} = \sum_{i \in i} \left(a_i \times Pg(i)_{MG}^2 + b_i \times Pg(i)_{MG} + c_i \right) \quad (1)$$

$$\text{Cost}_{t,i}^g = \lambda_i^{fuel} \frac{P_{t,i}^g}{\eta_i^g} \quad \forall i \in G, \forall t \in T \quad (2)$$

$$\text{Cost}_{t,i}^{chp} = \lambda_i^{fuel} \frac{P_{t,i}^{chp}}{\eta_i^{chp} LHV} \quad \forall i \in CHP, \forall t \in T \quad (3)$$

$$p_{t+1}^g - p_t^g \leq RU^g \quad \forall t \in T, \quad t \neq 24 \quad (4)$$

$$p_{t-1}^g - p_t^g \leq RD^g \quad \forall t \in T, \quad t \neq 1 \quad (5)$$

$$p_{t+1}^{chp} - p_t^{chp} \leq RU_e^{chp} \quad \forall t \in T, \quad t \neq 24 \quad (6)$$

$$p_{t-1}^{chp} - p_t^{chp} \leq RD_e^{chp} \quad \forall t \in T, \quad t \neq 1 \quad (7)$$

In the above formulations, Eq. (1) represents the calculation of the overall expense of electricity generation, which is determined by the production power of each microgrid (Pg) and the coefficients (ai), (bi) and (ci). Equations (2) and (3) represent the operational costs of the CHP and conventional diesel generator units. Further, Equations (4) through (7) outline the ramp-up and ramp-down limitations of both diesel generator and CHP units[37].

$$p_t^{ess} = p_t^{ess,dis} - p_t^{ess,ch} \quad \forall t \in T \quad (8)$$

$$p_t^{ess,dis} = \sum_{i=1}^{n_{bat}} p_{t,i}^{dis} \quad \forall t \in T \quad (9)$$

$$p_t^{ess,ch} = \sum_{i=1}^{n_{bat}} p_{t,i}^{ch} \quad \forall t \in T \quad (10)$$

$$0 \leq p_{t,i}^{dis} \leq \rho_{t,i}^{dis} \cdot p_i^{bat,max} \quad \forall i \in Bat, \forall t \in T \quad (11)$$

$$0 \leq p_{t,i}^{ch} \leq \rho_{t,i}^{ch} \cdot p_i^{bat,max} \quad \forall i \in Bat, \forall t \in T \quad (12)$$

$$p_{t,i}^{dis} + p_{t,i}^{ch} \leq 1 \quad \rho \in \{0,1\}, \forall i \in Bat, \forall t \in T \quad (13)$$

$$SoC_{t,i} = SoC_{t-1,i} - \frac{1}{p_i^{ess,max}} \left(\frac{1}{\eta_{conv,i}} \cdot p_{t,i}^{dis} - \eta_{conv,i} \cdot p_{t,i}^{ch} \right) \quad (14)$$

$$0 \leq SoC_{t,i} \leq 1 \quad \forall i \in Bat, \forall t \in T \quad (15)$$

Eq. (8) represents the battery power level, while Eq.s (9) and (10) describe the total charging and discharging power. Furthermore, Eqs (11–13) define the constraints on the charging and discharging power of the batteries, and Eq.s (14–15) illustrate the charging/discharging states within the batteries [37].

$$p_t^g = \sum_{i=1}^{n_g} p_{t,i}^g \quad \forall t \in T \quad (16)$$

$$0 \leq p_{t,i}^g \leq p_i^{g,max} \quad \forall i \in G, \forall t \in T \quad (17)$$

$$p_t^{chp} = \sum_{i=1}^{n_{chp}} p_{t,i}^{chp} \quad \forall t \in T \quad (18)$$

$$0 \leq p_{t,i}^{chp} \leq p_i^{chp,max} \quad \forall i \in CHP, \forall t \in T \quad (19)$$

Further, Eq.s (16) to (19) define the electrical power constraints for the conventional diesel generator and CHP generation units [37].

The total power transmission losses are given in Eq. 20.

$$loss = \sum_{i,j \in i} \left(Pg(i)_{MG} \times B(i,j) \times Pg(j)_{MG} \right) \quad (20)$$

Here, the equation of total power transmission losses is the sum of the power generation in each microgrid (Pg) by the transmission loss coefficients between microgrids (B(i,j)).

Equations (21) and (22) delineate the maximum and minimum limits of electricity generation. These constraints ensure that the electricity generation of each power plant adheres to specified bounds, preventing production levels from exceeding maximum capacities or falling below minimum thresholds.

$$Pg(i)_{MG} \leq P_{\max}(i) \forall i \in i \quad (21)$$

$$Pg(i)_{MG} \geq P_{\min}(i) \forall i \in i \quad (22)$$

Equation (23) shows the compatibility of electricity generation with load requirements.

$$\sum_{i \in i} Pg(i)_{MG} = Pd \quad (23)$$

This equation shows that the total electricity generation in all microgrids should be equal to the load requirements. Equation (24) expresses the compatibility of electricity generation with load and loss requirements.

$$\sum_{i \in i} Pg(i)_{MG} = Pd + loss \quad (24)$$

Equation (25) shows that the total electricity generation in all power plants must be equal to the sum of load requirements and losses.

$$\text{Minimize : compromise} = \sqrt{\left(\frac{\text{cost}}{\text{cost min}}\right)^2 + \left(\frac{\text{loss}}{\text{loss min}}\right)^2} \quad (25)$$

This equation quantifies the agreement value between cost and waste as the square root of the sum of squared deviations from their respective minimum values.

3- Probability Efficient Point (PEP) Method

The integration of Variable Renewable Energy (VRE) into the Day-Ahead Market (DAM) often leads to significant discrepancies between the forecasted and actual production levels [37]. The stochastic nature of VRE generation makes cost-effective DAM resource scheduling particularly challenging, especially when VRE output does not follow a predictable distribution. The PEP method can identify efficient points for VRE generation at specific confidence levels. The novel, data-driven mathematical approach proposed here [38] effectively determines PEPs using historical VRE generation data without assuming any specific probability distribution

function. The foundational concepts of the PEP method are outlined below [38].

Let $\tilde{\mathbf{p}} \in \mathbb{R}^{|R|}$ be a stochastic vector, and $\mathbf{v}, \mathbf{u} \in \mathbb{R}^{|R|}$ be two realizations. The probability distribution function $F_{\tilde{\mathbf{p}}}(\tilde{\mathbf{p}})$ and of the stochastic vector $\tilde{\mathbf{p}}$ is denoted as $F_{\tilde{\mathbf{p}}}(\mathbf{v}) = \Pr\{\mathbf{v} \geq \tilde{\mathbf{p}}\}$.

Description 1. If, $\forall \mathbf{v}_m \in \mathbf{v}$ and $\forall \mathbf{u}_m \in \mathbf{u}$, $\mathbf{v}_m \geq \mathbf{u}_m$, then $\mathbf{v} \geq \mathbf{u}$. Similarly, if $\mathbf{v} \geq \mathbf{u}$, then $\mathbf{v}_m \geq \mathbf{u}_m$.

Description 2. Let $\gamma \in (0,1)$. A point $\mathbf{v}^\gamma \in \mathbb{R}^{|R|}$ is named γ -efficient of $F_{\tilde{\mathbf{p}}}$ if $F_{\tilde{\mathbf{p}}}(\mathbf{v}^\gamma) \geq \gamma$ and none are present $\mathbf{u} \leq \mathbf{v}^\gamma$, $\mathbf{u} \neq \mathbf{v}^\gamma$ so that $F_{\tilde{\mathbf{p}}}(\mathbf{v}^\gamma) \geq \gamma$.

Aligned with Description 2, if $\mathbf{v}^\gamma$ represents the γ -efficient, then $F_{\tilde{\mathbf{p}}}(\mathbf{u}) \geq \gamma$ is equal to $\mathbf{u} \geq \mathbf{v}^\gamma$ at a probability state γ . In other words, a stochastic constraint $\Pr(\mathbf{u} \geq \tilde{\mathbf{p}}) \geq \gamma$. May be transformed into a definite limitation $\mathbf{u} \geq \mathbf{v}^\gamma$. The cornerstone of this transformation is calculating the PEP $\mathbf{v}^\gamma$ derived from historical data sets. Let $\mathcal{O}$ represent the deterministic set of historical sample realizations of the stochastic vector $\tilde{\mathbf{p}} = (\tilde{\mathbf{p}}_1, \dots, \tilde{\mathbf{p}}_m, \dots, \tilde{\mathbf{p}}_{|R|})$ for $|R|$ VRE locations in the distributed system. being the $\mathbf{p}^s = (p_1^s, \dots, p_m^s, \dots, p_{|R|}^s)$ show s^{th} sample from this set, and realization of $\tilde{\mathbf{p}}$, where $s \in S$. Let π^s denote the probability of each scenario s , where $\pi^s = P_r(\mathbf{p}^s = \tilde{\mathbf{p}}) > 0$ and $\sum_{s \in \mathcal{O}} \pi^s = 1$. According to [24], the program for solving PEP can be formulated as a Mixed-Integer Linear Program (MILP) in Eqs. (26)–(27).

The objective function in Eq. (26) denotes the element-by-element sum of the PEP vector $\mathbf{v}^\gamma$. The limitations mentioned in Eq. (27a) ensure that the cumulative probability of a group of selected samples is no less than γ . From this set of selected samples, limitation (27b) ensures that the minimal solution, aligned with Eq. (26), is selected, where every component of the solution ($\mathbf{v}_m^\gamma \in \mathbf{v}^\gamma$) is greater than the corresponding element of the historical data samples ($\mathbf{p}_m^s \in \mathbf{p}^s$). This is enforced through the binary variable $\mathbb{C}^s$, which equals ‘1’ if all constraints $\mathbf{v}_m^\gamma \geq \mathbf{p}_m^s$ (for $m = 1, \dots, |R|$), are satisfied in the s^{th} sample, and zero otherwise. It is important to note that since each historical sample vector $\mathbf{p}^s$ consists of different types of VRE units, assigning the binary variable $\mathbb{C}^s$ to the entire vector $\mathbf{p}^s$ respects the correlation between these technologies. The optimization program in Eqs. (26)–(27) ensures that an optimal solution is derived from the set of chosen samples, alluded to as the PEP, $\mathbf{v}^\gamma$. The component-wise sum of the PEP vector indicates the overall optimal quantity of system VRE generation at a specified probability level γ (confidence level $\alpha = 1 - \gamma$). According to Description 2, at a confidence level α , the VRE m located at node i is anticipated to produce an amount, $\mathbf{v}_m^\gamma$, which will be substituted for $\tilde{\mathbf{p}}_{i,t}^R$ in the power balance Eq. (24) to calculate the DLMP amounts.

It is important to highlight that the PEP method does not ensure a unique solution. However, considering the randomness of historical samples, as observed within our model, this lack of uniqueness seldom poses a problem. Nonetheless, if this scenario occurs, multiple PEP solutions can be found, and A scenario-oriented stochastic optimization framework can be used to solve the problem probabilistically [39,40].

$$\text{Minimize } \sum_{m=1}^{|R|} v_m^\gamma \quad (26)$$

Subject to:

$$\sum_{s \in \phi} \pi^s \$^s \geq \gamma, \quad (a)$$

$$v_m^\gamma \geq p_m^s c^s, \quad m=1, \dots, |R|, \quad s \in S \quad (b)$$

$$\$^s \in \{0, 1\}^{|\phi|}, \quad (c)$$

$$v_m^\gamma \in \mathbb{R}^+, \quad m=1, \dots, |R| \quad (d)$$

The historical daily production profiles for wind (W) and PV systems are shown in Figs. 5 and 6, respectively. According to the explanation given, 30 production scenarios related to PEP are shown in figures. For using the outputs generated by PEP, 4 cases are selected at confidence levels of 25%, 50%, 75% and 100% and the remaining cases are

shown as highlighted. The number of scenarios is reduced to 4 scenarios reduced using the confidence levels method, and the reduced scenarios are then applied to the optimization problem. Reducing the number of these scenarios is essential to ensure the optimization dimensions remain manageable.

4- Simulation Results and Discussion

4- 1- Evaluation of MG's operation

Considering Fig. 7(a), it is observed that, except two instances at the beginning and end of the interval, no significant changes in power generation occur in MG 4. This stability can be attributed to the reliance on fossil fuel power sources, such as diesel generators and CHP systems, which provide a consistent output. Additionally, the WTs equipped with maximum power point tracking (MPPT) systems and batteries maintain a stable generation profile between 08:00 and 16:00, unlike solar panels, which exhibit greater fluctuations during this period. This is because the operational cost of WTs is very low, so it is preferable to maximize production under any energy pricing offer. In contrast, MGs 2 and 3 exhibit variations in power generation between 08:00 and 14:00, attributable to the greater number of solar panels installed. During the period from 18:00 to 21:00, there is an increase in the energy discharged from the batteries, which contributes to an upward trend in the production curve. Conversely, MG

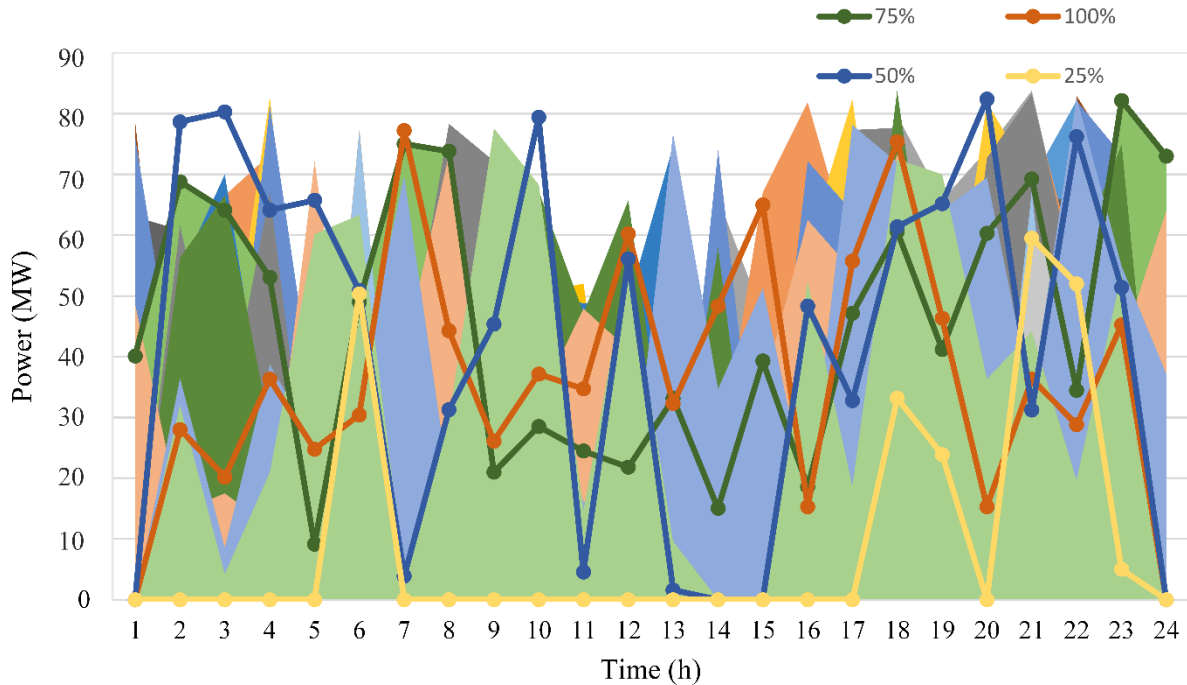


Fig. 5. Scenarios produced by PEP for WT

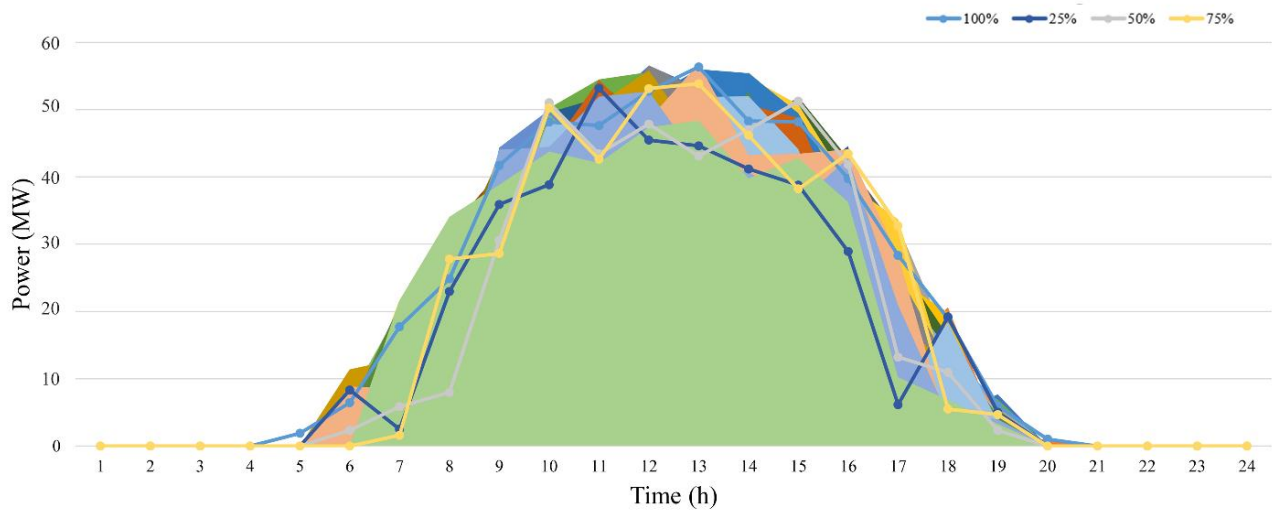


Fig. 6. Scenarios produced by PEP for PV

1 demonstrates fluctuations in power generation primarily due to the reliance on two diesel generators and the absence of MPPT systems in its WTs. However, it is noteworthy that between 08:00 and 14:00, MG1 achieves maximum power generation from PV panels due to the implementation of MPPT technology, while between 17:00 and 21:00, battery assistance further enhances power output. Additionally, as illustrated in Fig. 7(b), MGs 2 and 3 display the least variability in their production curves, indicating a more stable generation profile. However, MG 1 shows changes in its production due to the use of fossil fuel power sources. MG 4 also experiences fluctuations and reduced production levels between 05:00 and 09:00, as well as between 13:00 and 18:00. These changes are likely attributable to the operation of two CHP systems and two WTs, which affect the overall production curve. As illustrated in Figs 7(a), 7(b) and 7(c), effective resource management, energy storage, and responsive load strategies enable microgrids to inject active power into the main microgrid throughout operational hours, thereby capitalizing on financial opportunities within the energy market. However, during the early morning hours (01:00 to 03:00) and the final hours of energy planning (20:00 to 22:00), these microgrids tend to inject less active power into the MMG. This reduced output is primarily due to lower energy prices during these periods, coupled with elevated fuel costs associated with non-renewable energy sources. Such economic dynamics underscore the importance of strategic planning in optimizing energy production and market participation.

4- 2- Evaluation of MGs' Economic Status

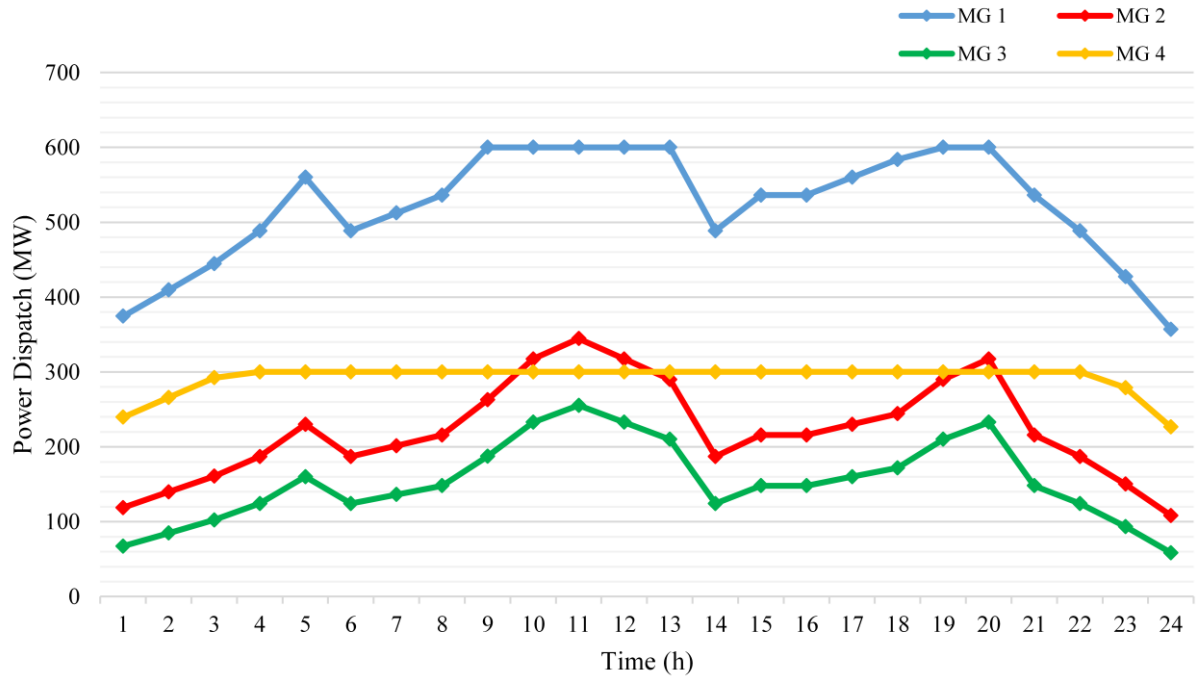
Figure 8 presents a comparative analysis of system costs under two scenarios: one without losses, with losses, and the other compromise-based approach. As illustrated in the

figure, system costs are notably higher during the periods of 08:00 to 12:00 and 17:00 to 21:00, which corresponds to increased energy demand during these hours, resulting in elevated prices. Conversely, the operational decisions of PV systems regarding energy delivery to the grid are influenced by strategies aimed at energy storage for enhanced economic benefits in response to price fluctuations. Unlike WTs, PV systems can store energy, allowing them to maximize production capacity between 08:00 and 14:00 while simultaneously charging batteries. Subsequently, during the peak pricing period from 17:00 to 21:00, these batteries discharge their stored energy into the grid. This strategy is further elucidated in Fig. 7. Moreover, Fig. 8 indicates that price increases occur across all time intervals, primarily attributed to system losses. This section highlights the impact of these losses on system prices over a 24-hour period, underscoring the importance of considering both demand dynamics and operational strategies in cost assessments.

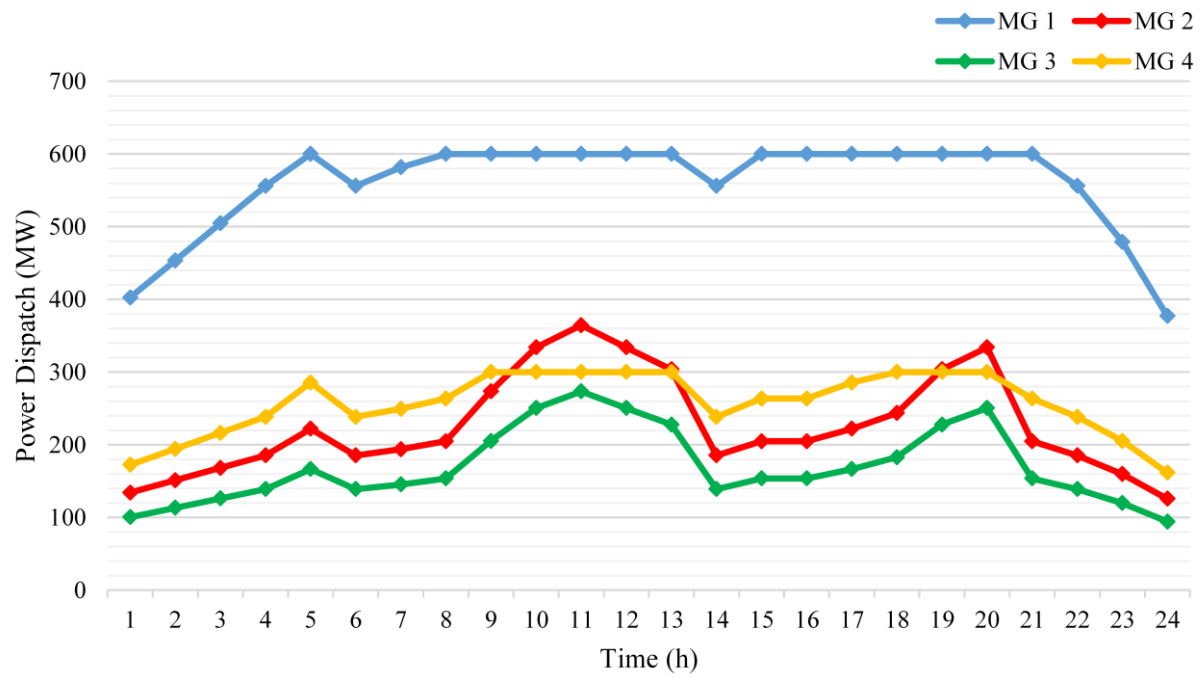
4- 3- Evaluating of the best compromise solution

Achieving a solution that simultaneously minimizes both cost and loss is practically infeasible. To address this challenge, a compromise objective function can be defined, which serves as a distance metric from the origin (0,0) to the cost-loss curve within a two-dimensional cost-loss coordinate system.

The compromise objective function is defined as outlined in Eq. 25. This equation allows for the determination of a compromise solution that effectively balances the trade-offs between cost and loss. By employing this approach, the inherent conflicts between minimizing costs and losses can be systematically navigated, ultimately leading to a more practical and achievable solution. Figure 7(c) and Fig. 8 illustrate the impact of the compromise

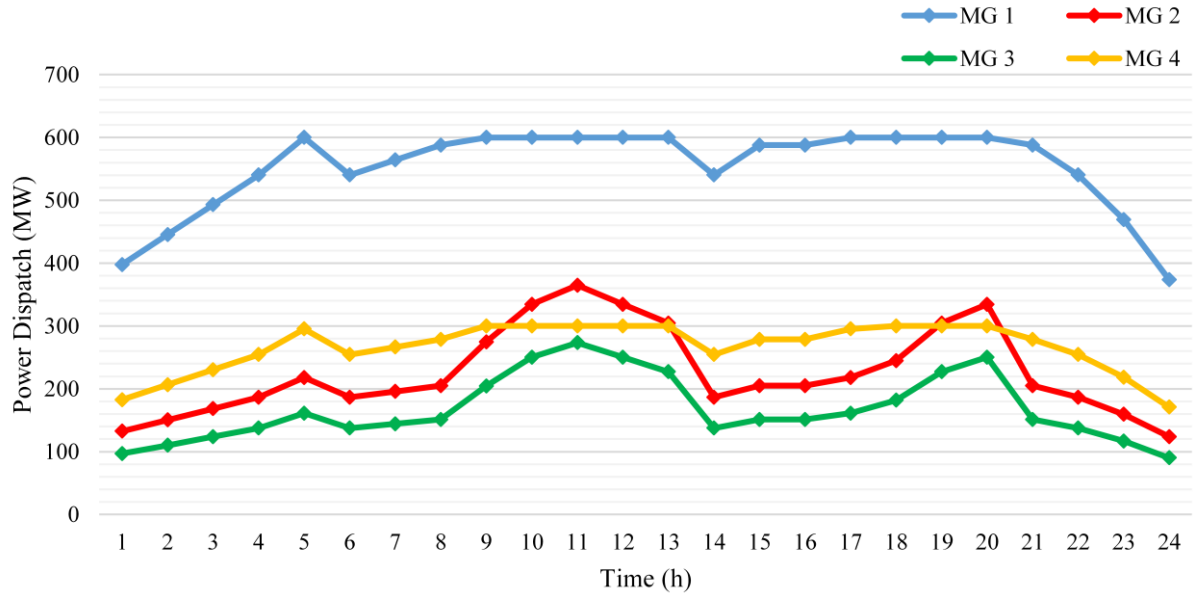


(a)



(b)

Fig. 7. Production and power distribution curve of the units: (a) ELD NL (b) ELD WL (c) COM DP (Continued)



(c)

Fig. 7. Production and power distribution curve of the units: (a) ELD NL (b) ELD WL (c) COM DP

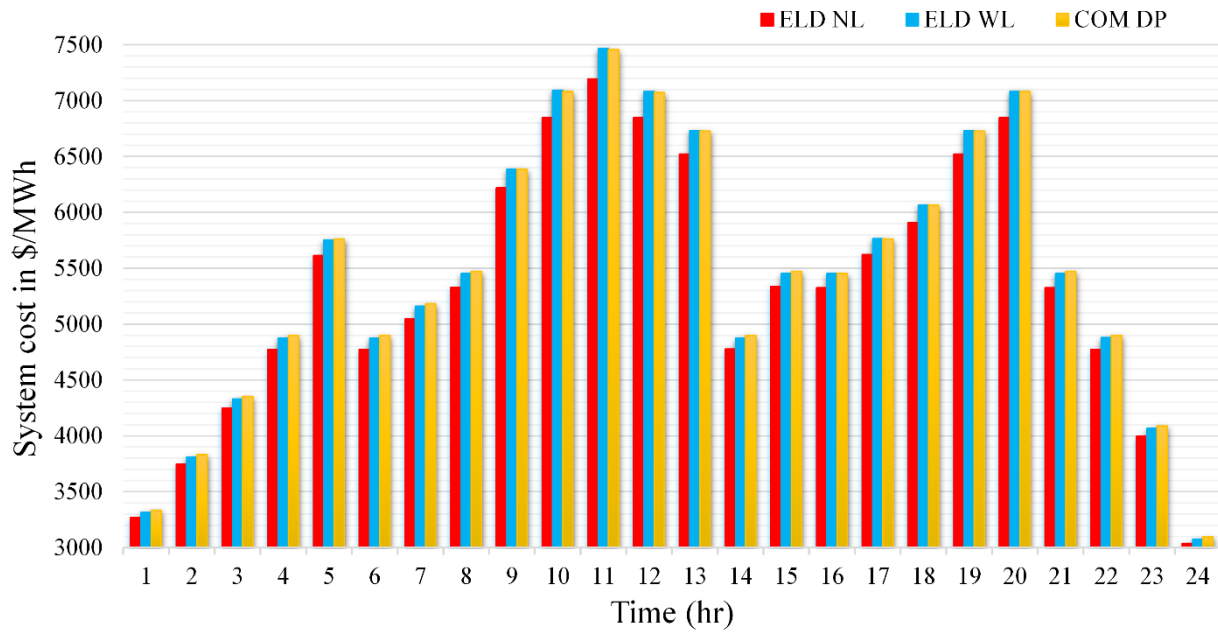


Fig. 8. Diagram cost of system for scenarios

function on unit production and system price. As shown in Fig. 7(c), for MG1, the production curve exhibits increased output during time intervals 5-8 and 14-18, deviating from the valley shape observed in Fig. 7(a). Consequently, a smoother power production curve is observed. However, due to computational losses, the power output during intervals 5-8 and 14-18 is slightly reduced compared to the minimum loss state (Fig. 7(b)). For MG4, a minor decrease in production is observed during the interval 20-24 due to the introduction of system losses. In contrast, MG2 and MG3 exhibit minimal changes owing to their reduced reliance on PV systems and the incorporation of MPPT systems and ESS.

As shown in Fig. 8, the system price increases compared to the previous states. However, due to the compromised objective function, this increase is marginal. Notably, the least price deviation occurs during intervals 9-13 and 18-20, attributable to the utilization of PV and battery systems, which minimize losses during these periods. Conversely, the most significant price deviation is observed during the interval 21:00-24:00.

4- 4- Sensitivity Assessment of System Costs and Losses under Operational

In this section, a comprehensive sensitivity analysis is conducted to evaluate the performance of the proposed methodology. The primary objective is to establish a well-structured balance and achieve a rational trade-off between two fundamental indices in power system operation, namely the overall operating cost and the total network losses. These two indicators simultaneously reflect the economic and technical dimensions of power system planning and operation, thereby serving as key benchmarks for assessing system efficiency. As formulated in Eq. (25), the problem can be characterized as an optimization, where it is practically infeasible to attain the absolute minimum of both indices simultaneously. In other words, a reduction in one parameter inherently leads to an increase in the other. Consequently, the focus of the proposed

approach is to determine an optimal compromise solution that ensures an efficient balance between technical performance and economic feasibility. To systematically investigate this trade-off, the sensitivity analysis has been carried out under three distinct scenarios: minimum achievable cost, actual system cost, and compromise-based cost. An analogous evaluation has also been performed for the network losses, considering the same three operating scenarios. The results of these analyses are illustrated in Figs 9 and 10.

According to Fig. 9, the maximum cost values in all three scenarios predominantly occur during the time intervals of hours 5-6, 9-15, and 19-20, which correspond to high-demand periods. It can be observed that the system cost under the compromise-based approach is nearly aligned with the minimum achievable cost. More specifically, the compromise scenario results in a 3% reduction compared to the actual system cost, while exhibiting only a 0.7% increase compared to the minimum cost case. Similarly, Fig. 10 demonstrates that system losses also peak within the same time intervals. In this regard, the compromise-based solution achieves a 2.5% reduction in losses compared to the actual system, with merely a 0.6% increase relative to the minimum-loss scenario.

These findings clearly highlight the effectiveness and robustness of the proposed methodology, as the considerable reductions in both operating cost and losses relative to the actual system far outweigh the marginal increases compared to their absolute minima. This confirms that the compromise-based strategy provides a practical and technically sound balance between conflicting objectives. Moreover, it should be emphasized that, in operations mode, minimizing system cost inherently increases network losses, and vice versa. Thus, achieving a simultaneous reduction in both metrics represents a major challenge in power system optimization. Nonetheless, the obtained results demonstrate that the proposed framework successfully addresses this challenge by delivering a stable, efficient, and economically justified solution for modern power system operation.

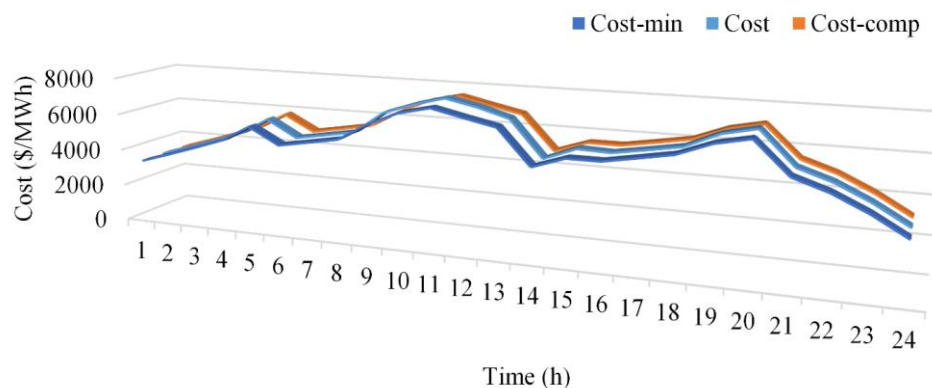


Fig. 9. Sensitivity analysis of system costs under varying operational

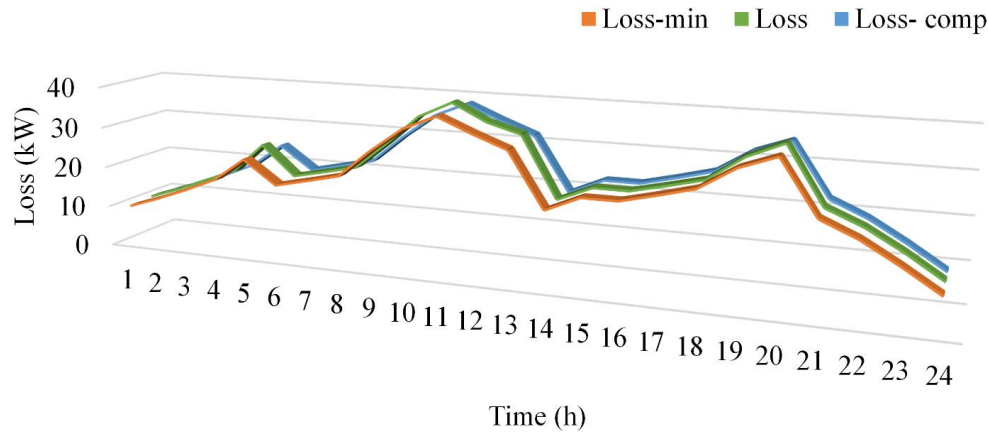


Fig. 10. Sensitivity analysis of system losses under varying operational

5- Conclusions

This study presents an advanced energy management strategy for MGs within the framework of a MMGs system, explicitly considering the participation of MGs in energy markets. A novel optimization problem has been formulated, incorporating two primary objectives: minimization of energy cost and losses alongside a compromise-based objective function designed to balance these conflicting goals. Numerical evaluations demonstrate that the proposed compromise strategy effectively reduces both system costs and network losses. Specifically, in the case of power generation among MGs, MG4 exhibited the largest fluctuations across the three studied scenarios, which can be attributed to the integration of WTs and the associated variability in their output.

Furthermore, simulation results highlight that the system cost under the compromise-based approach closely aligns with the minimum achievable cost. In this regard, during peak demand periods, the compromise scenario achieves a 3% reduction compared to the actual system cost, while incurring only a marginal 0.7% increase relative to the absolute minimum-cost case. Similarly, system losses, which peak during high-demand intervals, are reduced by 2.5% in the compromise-based solution compared with the actual system, with only a 0.6% increase relative to the minimum-loss benchmark.

These findings clearly underscore the effectiveness and robustness of the proposed method. The reductions achieved relative to the actual system substantially outweigh the marginal increases observed against absolute optimal benchmarks. This confirms that the compromise-based optimization strategy successfully delivers a technically sound and economically practical trade-off, ensuring balanced improvements across conflicting system objectives.

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