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Optimum Positioning and Sizing of Biomass Distributed Generators for Real Power Transmission Congestion Management

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Power transmission congestion is a critical challenge in power systems, especially with growing demand and decentralized generation.*
- *Distributed generators (DGs), including renewable sources, can help mitigate congestion by supplying power locally.*
- *Most studies focus on solar or wind DGs, and often assume standard test systems without incorporating real-world data or practical constraints.*

WHAT DOES THIS STUDY ADD ON THIS TOPIC?

- *This study proposes an improved optimization framework using a Grey wolf Optimization algorithm for determining the optimal size and location of*

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ABSTRACT

The energy market today allows for bidirectional transactions between utilities and consumers, even within traditional practices. Factors like generator failures, maintenance of transmission lines, and high network demand can cause overheating and failures in transmission lines and equipment, resulting in contingencies within the transmission network. Methods like load shedding, rescheduling of generators, and insertion of renewable energy-based distributed generators (DGs) are various alternatives for alleviating congestion in the network lines, i.e., the transmission lines or other network elements operate at or beyond their designed capacity, restricting the flow of electricity. In this work, the insertion of renewable energy DGs at their optimal location is proposed as a novel approach for alleviating the congestion in the network lines. Firstly, the real power transmission capability distribution factors are evaluated to determine the optimal location for integrating the renewable energy DGs concerning the congested line. Furthermore, these types of DGs, which are solar, wind, and biomass, are considered along with the modeling of uncertainties in the solar and wind. The Beta and the Weibull probability distribution functions are employed to explore the uncertainty in solar and wind DGs, respectively. Furthermore, the optimal capacity of Biomass DG has been obtained by minimizing real power losses and the voltage stability margin chosen for alleviating the congestion in the network lines. The newly evolved algorithm, Grey Wolf Optimization, has been employed to solve the multi-objective optimization problem of interest. The performance of Grey Wolf - Multi-Objective Optimization is verified on a standard IEEE-30 (Institute of Electrical and Electronics Engineers) bus system to demonstrate the effectiveness of the proposed approach. Results show that the size of biomass DG and real power losses are obtained as 9.9533 MW and 9.3055 MW, respectively.

***Index Terms*—**Biomass distributed generations, probability distribution function, renewable sources

I. INTRODUCTION

The existing state of conventional power production cannot meet the emerging electricity requirements on an international scale. Due to inadequate system design, 16% of people on the planet still live without access to electricity [1]. In transmission, network congestion management (CM) is a very crucial problem. Power transmission lines can become congested due to various factors such as generator outages, transmission line failures, and transformer maintenance. As a result, while customers can still access power, the transmission lines may exceed their operational limits, potentially violating power flow constraints. This situation is called power transmission congestion [2]. In the transmission network, congestion reduces the power transfer capacities of lines, drives up prices, and prevents the most efficient supply from getting to distributors because it overloads the system to its upper limit capability.

Multiple CM strategies are put forward and utilized by energy consultants in the power sector as well as researchers in the literature. To start, heuristic algorithms are used to mitigate congestion. Secure transactions for the hybrid market model take into account the effect of flexible alternating current transmission system technology on the oversight of transmission network overcrowding, along with the most appropriate scheduling of generators while considering the effect of liability limitations. Distribution scheme operators (DSOs) must evaluate and optimize their *biomass-based DGs to relieve real power congestion.*

- *It incorporates real- time data of solar and wind, bridging the gap between theoretical models and practical application.*
- *The study demonstrates that biomass DGs, when optimally placed, significantly reduce power losses and congestion.*

asset investment costs to minimize investments by adopting smart grid functions. The maximum penetration of plug-in electric vehicles in the distribution system to minimize overall costs and the charging coordination of grid-to-vehicle and vehicle-to-grid (G2V-V2G) modes is designed [3].

When distributed energy resources (DERs) are heavily included in a distribution network, the DSO can utilize the dynamic tariff method to mitigate potential congestion. Integrating combined heat and power systems into microgrids is crucial for improving overall energy efficiency. Optimizing the dispatch of these systems can significantly reduce greenhouse gas emissions while ensuring economic viability by using the Harris Hawks Optimization algorithm, as highlighted in [4]. The day-ahead scheduling of distributed generation owners, air conditioning loads, demand response aggregators, and DERs into the day-ahead wholesale market in a system run by a DSO is covered in [5]. For the first time, integrated transmission expenditure allotment methods like Postage Stamp and Contract Path are used. Furthermore, flow mile technologies are used, including MVA-MILE and MW-MILE. The development of flow cost techniques like MVA-COST, MW-COST, and MW-COST is the last step [6].

For the power system comprising thermal and wind energy generating units, a proposed metaheuristic-based optimization strategy for tackling the combined economic emission dispatch problem has been developed as mentioned in [7] however, the study may not fully account for wind energy variability, potentially affecting solution reliability. Additionally, the optimization model might be limited to specific geographical or operational conditions, reducing its generalizability to other power systems. The main objective of the optimal setup procedure is to minimize daily power losses. As of now, DG capabilities have been calculated using either financial or technical parameters, each of which indicates that the system's financial burden or technical execution is compromised, but the model may not consider the economic implications of large-scale deployment of solar and wind technologies, such as initial investment costs and maintenance in [8]. Similarly, several studies that attempted to connect green energy DGs to the present system neglected to deal with the probabilistic nature and necessary capabilities. The performance of Grey Wolf Optimization (GWO) may vary significantly depending on the specific problem domain and parameter settings, which could affect its robustness in [9]. To reduce the cost of rescheduling and the overall change in power after rescheduling, two proposed variants of Monarch Butterfly Optimization (MBO) are utilized to reschedule the generators: chaos-embedded MBO (CHMBO) and Improved MBO with a linear weighting factor (IMBO-LW) in [10] but the effectiveness of this algorithm may be influenced by the specific characteristics of the power system being analyzed. Likewise, a distributed energy storage system combines battery-powered energy storage with solar-powered distributed generation, but the study may not fully explore the impact of varying energy storage technologies on the overall effectiveness of CM strategies in [11]. The study then introduces the interval calculation approach to account for the intermittent nature of solar distributed generation and make it available during periods of peak load, thus improving the network's overall efficiency. Within [12], a novel topology control technique is developed to improve security margins in a power network by lowering overloads and congestion; however, the study might not address the potential impacts of such dynamic reconfigurations on system stability and reliability. Similarly, various transmission congestion issues and events in the energy industry are addressed by concentrating on the problems and effects of electrical power congestion have been addressed in [13] but the analysis may not account for regional variations in congestion issues, limiting its applicability to specific geographical contexts. The transmission congestion problem has been addressed using the Improved Manta-Ray Foraging Optimization intended to minimize the congestion cost, but it does not extensively evaluate the computational efficiency of the proposed method in large-scale networks in [14].

In addition to the above, the importance of integrating market mechanisms with Transmission System Operators and DSOs to enhance CM in power systems has been deliberated in [15], but the analysis may not fully address the potential economic impacts on consumers and market participants resulting from the proposed coordination strategies. As a result, the study may overlook the variability of renewable energy sources and their influence on market dynamics, potentially impacting the effectiveness of the proposed coordination framework. Further, a flexibility platform developed for DSOs that utilizes an optimal CM model is proposed in ref. [16] However, the model's applicability may be limited to European contexts, potentially reducing its relevance in other regions with different regulatory and market structures. The platform aims to enhance the operational efficiency of power systems by integrating flexible resources and improving

CM strategies within the European CoordiNet project framework. The model's applicability may be limited to specific geographical regions or regulatory environments, potentially reducing its generalizability to other contexts. A substation reconfiguration selection algorithm that employs Power Transfer Distribution Factors (PTDFs) and a reinforcement learning approach to manage congestion effectively is proposed in ref. [17] as the reliance on PTDFs may limit the algorithm's performance in highly dynamic systems where real-time data is critical for accurate CM. Further, a sensitivity-based generation rescheduling approach is proposed to alleviate congestion in network lines in [18], with the aim of minimizing congestion costs while ensuring system reliability. The optimization algorithm's performance may be sensitive to initial conditions and may not guarantee convergence to the global optimum, potentially affecting the effectiveness of CM.

The firefly algorithms have been utilized to determine the optimal capacity of DG for effective transmission CM [19]. However, the study may not fully explore the economic implications of integrating DG into existing power systems, particularly regarding investment costs and regulatory hurdles. Factors such as infrastructure limitations, regulatory barriers, and market dynamics contribute to electrical power congestion in the sector. This highlights the need for enhanced transmission infrastructure and supportive policies to effectively address and mitigate congestion issues [20]. The study may not account for the impact of emerging technologies such as energy storage systems and smart grid solutions on CM. Additionally, it may lack empirical data from diverse geographical regions, limiting the generalizability of the findings.

A hybrid swarm optimization approach is presented to determine the optimal capacity of DG sources to manage transmission congestion effectively [21]. The study primarily focuses on simulation results, which may not fully capture real-world complexities and uncertainties in power system operations. Furthermore, the scalability of the hybrid optimization method in larger systems remains untested. A modified whale optimization algorithm is used to optimize the placement and operation of wind farms, demonstrating that wind energy can alleviate congestion and improve overall system efficiency [22]. The study may not consider the variability and intermittency of wind energy, which could affect the reliability of CM strategies. Additionally, the model's assumptions regarding wind resource availability may limit its applicability in regions with different wind profiles. A framework is proposed using multi-objective demand-side management strategies that incorporate consumer behavior and renewable energy sources, demonstrating significant improvements in cost savings and emissions reduction [23]. The study may not fully address the complexities of consumer behavior and its impact on demand-side management strategies. Furthermore, the proposed framework's effectiveness in larger, more diverse microgrid settings remains to be validated. Various methodologies for optimal planning, including mathematical modeling, heuristic approaches, and simulation techniques, are proposed [24]. Factors influencing the deployment of DG and Energy Storage Systems, including economic viability, regulatory frameworks, and technological advancements, are also discussed. The review identifies gaps in current research, particularly in the integration of renewable energy sources with existing power infrastructure. Different optimization techniques, including genetic algorithms, particle swarm optimization, and mixed-integer linear programming, have been addressed for the present problem of interest [25]. The review emphasizes the role of DG in improving voltage profiles, reducing losses, and enhancing the overall reliability of power systems. Environmental impacts and regulatory considerations are also addressed, highlighting the need for sustainable practices in DG deployment.

In order to expand the performance of the network under deliberation using multi-objective optimization (MOO), an effort was made to obtain DG sizes, which is a significant addition to the existing CM problem. Similar to how renewable energy DGs like solar and wind have an intermittent nature, PDF modeling has been used to simulate these DGs' integration with the current system [6]. Furthermore, a MOO framework is used to evaluate and solve the controlled output of the biomass DG with the help of GW-MOO. Transmission line congestion decreases as GWO distributes the load more effectively by optimizing the power flow. Grey Wolf Optimization improves the power grid's stability and dependability by controlling congestion. Real-time CM relies on timely solutions, which are ensured by the algorithm's quick convergence speed. Biomass DG uses renewable resources, reducing reliance on fossil fuels and supporting decarbonization. Biomass DG is dispatchable, aiding in peak demand management and grid stability. Localized power generation reduces transmission congestion and losses, making biomass-based DG a suitable choice for this work.

A comprehensive review of recent literature indicates that the challenges faced by the grid include the rising integration of variable renewable energy sources, such as solar and wind, which results in generation fluctuations and congestion during peak production periods. Limited energy storage capacity restricts the ability to smooth out fluctuations and relieve congestion. Congestion often requires complex operational adjustments that may not be feasible in real time. Therefore, developing advanced optimization algorithms, such as those based on artificial intelligence, can improve operational efficiency and decision-making under constraints to reduce congestion. While there is existing research on biomass energy systems and variable renewable energy sources like solar and wind, there is limited literature on specific integration strategies that optimize the operation of biomass DG in conjunction with these variable sources. Investigating how biomass can complement solar and wind energy during periods of low generation could provide valuable insights. There is a need for more research on innovative technologies and control mechanisms that can enhance the reliability and efficiency of biomass DG when paired with solar and wind energy. Most of the researchers considered multi-objective problems, but single-objective problems are not considered, which is also important. Considering the above, the major contributions of the present work are as follows:

1. In this work, the transmission CM problem has been addressed by incorporating optimal capacity biomass DG at a suitable location.
2. Secondly, the capacity of biomass DG is assessed considering the stochastic behavior of solar and wind DGs, modeled using real-world data and represented by Weibull and Beta PDFs—an approach that integrates practical uncertainty into the planning process.
3. Further, the positioning of the DGs is evaluated based on real-time distribution factors, which are derived from a Jacobian matrix of Newton–Raphson load flow.
4. Finally, a novel and efficient GWO has been proposed to determine the optimal capacities of Biomass DG for relieving network congestion. Unlike the conventional GWO, the proposed

method integrates probabilistic models of solar and wind DGs using Beta and Weibull distributions, incorporates a customized objective function focused on minimizing congestion and losses, and employs adaptive control parameters to improve convergence speed and accuracy. Additionally, an enhanced constraint-handling mechanism ensures compliance with power system operational limits, making the approach both practical and robust.

5. This methodology is validated using a standard IEEE-30 bus system, demonstrating its effectiveness in minimizing power flows in congested lines and improving voltage profiles while reducing potential power losses. The main advantage of this work is that optimization is always reached without violation of the objectives and constraints.

Several studies have focused on the optimal placement and sizing of DG in power distribution systems to enhance performance and efficiency. For instance, Kumar et al. [25] provided a comprehensive review of techniques for optimal DG allocation, highlighting various methodologies used across different scenarios. Gampa and Das [26] addressed DG allocation considering average hourly load variations, which is essential for modeling real-world demand patterns. Similarly, Ing et al. [27] investigated operational modes of DG and their impact on network safety margins and reliability.

While these studies contribute valuable insights into DG optimization, they often lack a detailed consideration of the probabilistic behavior of renewable energy sources. In contrast, this study models solar and wind DGs using Beta and Weibull probability distribution functions, respectively, thereby reflecting the stochastic nature of renewable energy sources more accurately. Furthermore, the capacity of biomass DG is evaluated under this probabilistic environment, which is relatively underexplored in previous research.

In terms of optimization techniques, the GWO has been widely adopted in multi-objective frameworks, as demonstrated by Mirjalili et al. [28], who proposed a GW-MOO for solving complex optimization tasks. Similarly, Peesapati et al. [29] addressed CM through MOO using the Flower Pollination Algorithm. Building on these foundations, this study utilizes both single-objective and MOO approaches: single-objective for optimal sizing of biomass DG, and multi-objective formulations for comparing trade-offs among system performance metrics such as power loss, voltage profile, and congestion. This dual-framework approach offers a more comprehensive and practical decision-making strategy for planning distributed generation in modern power systems.

These distinctions establish the novelty and contributions of this work by integrating probabilistic renewable models with biomass DG optimization, using both single and multi-objective GWO-based approaches.

The remaining sections of the manuscript are organized as follows: Section 2 formulates the congestion problem, while Section 3 presents the optimal distribution of DGs. A probabilistic model representing DGs for renewable energy analysis is outlined in Section 4. Section 5 details the Grey Wolf MOO used to address the multi-objective function. The findings from the case study are discussed in Section 6, and Section 7 provides the conclusion.

II. CONGESTION PROBLEM

In a deregulated economy, bilateral and multilateral dealings are more important [2]. The following is a representation of the bilateral transaction (1):

$$P_g^i - P_d^j = 0 \tag{1}$$

Where bus *i* hosts the power generation P^i_g, while bus j corresponds to the contracted power demand P^j_d. By maximizing social welfare within practical bounds, the marketplace is cleared in double-sided bidding. Next, the independent system operator evaluates the safety of the electricity system. In the event of system instability, CM is implemented, and several generators may be instructed to alter their output. As a consequence, in a situation of overcrowding, the generators could earn more or suffer a greater loss. To mitigate congestion, it is recommended to install optimally sized biomass distributed generation (BMDG) units at strategic load pockets. The unpredictability of solar and wind needs to be taken into account while calculating the optimal sizes of the BMDG because distributed generation from solar and wind is entirely dependent on geography. This multi-objective problem is used to find out the optimal sizes, with the primary objectives of loss margin (LM) and voltage stability margin (VSM).

A. Fuel Cost of Generators

Thermal generators, as conventional sources, are already part of the existing grid to ensure reliable load satisfaction. Their inclusion provides a realistic representation of current network conditions. While biomass, solar, and wind are used to mitigate transmission congestion, their variable nature requires the stable support of thermal generators to maintain grid reliability. Including them allows for a comprehensive assessment of how renewables interact with existing infrastructure to reduce congestion without compromising system stability.

The fuel cost of the thermal generators is expressed in terms of the sum of the individual quadratic cost functions of each generator. It is expressed as below by equation (2) [6]:

$$F_i = \sum_{i=1}^{N_g} \frac{1}{2} a_i P_i^2 + b_i P_i + c_i \tag{2}$$

where F_i is the fuel cost of generators, P_i is the real power generation i^{th} generator, and a_i, b_i, c_i are the cost coefficients of i^{th} generator.

B. Loss Margin

This objective focuses on minimizing power losses in the distribution system, which can enhance the overall efficiency of the system [6]. A higher LM indicates that the system can handle more load without significant losses given in equation (3).

$$Minimize\,LM = \frac{Ploss^{dg}}{Ploss^{0}} \tag{3}$$

Where $Ploss^{dg}$ is the real power losses after inserting the DG, and $Ploss^0$ is the real power losses before inserting the DG.

C. Voltage Stability Margin

This objective aims to modify the voltage stability of the system, ensuring that voltage levels stay within standard limits under variable load situations [6]. A higher VSM indicates a more robust system capable of maintaining voltage stability shows in (4).

$$\mathrm{minVSM} = \frac{\sum_{i}^{N}(V_i^{DG} - 1.0)^2}{\sum_{i}^{N}(V_i^{0} - 1.0)^2} \tag{4}$$

V^{DG}_i is the voltage at the i^{th} node after connecting the DG, V^0_i is the voltage at the i^{th} node before connecting the DG, and N is the number of buses.

D. Constraints

a) *Equality Constraints (5,6)*

$$P_{gP} - P_{dP} = V_P \sum_{N=1}^{nbus}\left\{\left(GP_{PN}\cos\delta_{PN} + B_{PN}\sin\delta_{PN}\right)V_N\right\} \tag{5}$$

$$Q_{gP} - Q_{dP} = +V_i \sum_{j=1}^{nbus}\left(-B_{PN}\cos_{\delta PN} + G_{PN}\sin_{\cdot\, PN}\right)V_N \tag{6}$$

a) *Inequality Constraints (7-12)*

$$P_{gP}^{min} \le P_{gP} \le P_{gP}^{max} \tag{7}$$

$$Q_{gP}^{min} \le Q_{gP} \le Q_{gP}^{max} \tag{8}$$

$$V_P^{min} \le V_P \le V_P^{max} \tag{9}$$

$$\delta_P{}^{min} \le \delta_P \le \delta_P{}^{max} \tag{10}$$

$$S_l \le S_l^{max} \tag{11}$$

a) *DG Constraints*

$$0 \le P_{DG,k} \le P_{DG}{}^{max} \tag{12}$$

Where P_{gP}^{min} is the minimum active power generation of each generator, P_{gP}^{max} is the maximum active power generation of each generator Q_{gp}^{min} is the minimum reactive power generation of each generator, Q_{gp}^{max} is the Maximum reactive power generation of each generator, V^{min} is the minimum voltage limits of buses, V^{max} is the maximum voltage limits of buses, δ_i is the voltage angles of i^{th} bus, $\delta_i{}^{max}$ is the maximal limitation of voltage angles of i^{th} bus, $\delta_i{}^{min}$ is the minimal limitation of voltage angles of i^{th} bus, S_l^{max} is the maximum permissible MVA line flow in line. $P_{DG}{}^{max}$ is the maximum power generation of DG.

The multi-objective function, which has several goals, is depicted as follows (13):

$$Minimize\,F = W1*LM + W2*VSM \tag{13}$$

Equations (3) and (4) show single-objective functions, whereas (13) shows a multi-objective function. The constraints in the aforementioned equations as well as the following constraints are applied to the aforementioned fitness function. Weight factors W_1 and W_2 are considered 0.5, respectively, as equal priority is given to a single objective while considering a multi-objective problem, whereas 1 and 0 will be considered while solving a single objective equation and vice versa (14).

$$\sum_{n=1}^{T} W_n = 1 \tag{14}$$

Where W_n is the n_{th} Weight factor, T is the total number of objectives.

Further, after the incorporation of PV, wind, and biomass DGs at a suitable location, the modified power flow equation is shown as below (15):

$$P_{gP} + P_{DG,k} - P_{dP} = V_P \sum_{N=1}^{nbus}\left\{\left(GP_{PN}\cos\delta_{PN} + B_{PN}\sin\delta_{PN}\right)V_N\right\} \tag{15}$$

III. ALLOCATION OF DISTRIBUTED GENERATORS AT THE OPTIMAL LEVEL

A ZBUS-based contribution component-supported method is suggested for the insertion of the DG to reduce congestion. Similarly, the ideal position for DGs is determined using the RPTCDFs suggested in [26]. It is the ratio of the change in power insertion (Pn) at a specific bus n to the alteration in real power flow (Pij) along a transmission line connecting buses P and N. The power flow and transfer capacities of various nodes in the transmission network are depicted clearly by RPTCDFs. It is easy to identify nodes where adding distributed generation will significantly reduce congestion or enhance transfer capacity by examining these parameters. They provide sensitivity analysis, which examines the effects of minute adjustments to power injection or withdrawal at different nodes on the system as a whole. This can identify the precise places where DG will be most helpful [6]. The RPTCDFs for line *k* are shown mathematically as follows (16).

$$RPTCDF_n^K = \frac{P_{PN}}{P_n} \tag{16}$$

It is possible to express the actual power flow in a line-k connected to buses-i and-j as follows (17):

$$P_{PN} = V_P V_N Y_{PN} \cos\left(_{PN} + \delta_N - \delta_P\right) - V_P^2 Y_{PN} \cos_{PN} \tag{17}$$

The magnitude and angle of the ij^{th} element in the Ybus matrix are YPN and PN. Using Taylor series approximation, the following equation (18) can be used to represent this one (ignoring second and higher order terms) [6]:

$$P_{PN} = \frac{P_{PN}}{\delta_P}\delta_i + \frac{P_{PN}}{\delta_N}\delta_j + \frac{P_{PN}}{V_P}V_i + \frac{P_{PN}}{V_N}V_N \tag{18}$$

Equation (15) can be written as (19):

$$P_{PN} = \alpha_{PN\delta P} + b_{PN}\delta_N + c_{PN}V_P + d_{PN}V_N \tag{19}$$

The partial derivatives of the real power flow with respect to the variables δ and V can be utilized to create the coefficients appearing in (19) as (20-23):

$$\alpha_{PN} = V_P V_N Y_{PN} \sin\left(_{PN} + \delta_N - \delta_P\right) \tag{20}$$

$$b_{PN} = -V_P V_N Y_{PN} sin\left({}_{PN} + \delta_N - \delta_P \right) \tag{21}$$

$$c_{PN} = V_N Y_{PN} cos\left({}_{PN} + \delta_N - \delta_P \right) - 2V_P Y_{PN} cos_{PN} \tag{22}$$

$$d_{PN} = V_P Y_{PN} cos\left({}_{PN} + \delta_N - \delta_P \right) \tag{23}$$

RPTCDFs have been ascertained by using the subsequent Jacobian relationship (24)

$$P = J_{11}\delta + J_{12}V \tag{24}$$

When P-V coupling is disregarded, (24) can be expressed as (25):

$$P = J_{11}\delta \tag{25}$$

From (23), we get (26),

$$\delta = \left[J_{11}\right]^{-1}\left[P\right] = \left[M\right]\left[P\right] \tag{26}$$

So, using the following equation (27-28),

$$\delta_P = \sum_{l=1}^{n} m_{Pl} P_l \tag{27}$$

$$P = 1, 2, \ldots n, Ps \tag{28}$$

where V_l is the l^{th} bus voltage magnitude, δ_l is the l^{th} bus voltage angle, Y_{pn} is the admittance magnitude of the element p-n in Ybus, and θ_{pn} is the admittance angle of the element p-n in Ybus [6].

The effect of changing the bus voltage on the potential power rate is thought to be nominal. Since real power must be taken into account while calculating DGs due to the relationship between reactive power and voltage in a power system, Equation (28) can be rewritten as (29):

$$P_{PN} = \alpha_{PN}\delta_P + b_{PN}\delta_N \tag{29}$$

Substituting (26) into (28), we get (30):

$$P_{PN} = \alpha_{PN} \sum_{l=1}^{n} m_{Pl} P_l + b_{PN} \sum_{l=1}^{n} m_{Nl} P_l \tag{30}$$

Equation (28) is represented as (31):

$$P_{PN} = \left(\alpha_{PN} m_{P1} + b_{PN} m_{N1}\right) P_1 + \left(\alpha_{PN} m_{N2} + b_{PN} m_{N2}\right) P_2 + \ldots\ldots\ldots + \left(\alpha_{PN} m_{Pn} + b_{PN} m_{Nn}\right) P_n \tag{31}$$

Equation (28) can be represented as (32-33):

$$P_{PN} = RPTCDF_2^K P_1 + RPTCDF_2^K P_2 + RPTCDF_n^k P_n \tag{32}$$

$$RPTCDF_2^K = \alpha_{PN} m_{P1} + b_{PN} m_{N1} \tag{33}$$

RPTCDF is a real distribution multivariate for transmission overcrowding that is equal to bus n and line *k* that links bus P and bus N [6]. The Jacobian utilized in this study to calculate the RPTCDFs will change when the system's operational conditions vary [30]. However, the suggested method can be used to update the RPTCDFs and is fairly quick. The values that were obtained are then organized in descending sequence to identify the buses to be implemented in order, depending on the DGs.

IV. PROBABILISTIC MODEL FOR THE PRODUCTION OF RENEWABLE ENERGY

The location has a huge impact on how much energy is produced by the sun and wind. As a result, these renewable energy sources' outputs are variable. In contrast, the output of biomass generation is continuous and will only be adjusted as necessary. In this work, solar and wind-based energy DGs are considered non-dispatchable DG, whereas biomass is considered dispatchable DG, i.e., dispatchable DG. It is necessary to analyze the characteristics of solar irradiation and wind velocity for the best performance of solar panels and wind turbines. Therefore, it is necessary to choose a PDF that produces correct results. For modeling renewable sources, the Beta Probability Distribution Factor (BPDF) and Weibull Probability Distribution Factor (WPDF) are frequently utilized [27].

A. Model for Solar Power Generation

According to BPDF [27], solar irradiation is assumed to be probabilistic, as solar radiation is a broad term referring to the overall energy output from the Sun, while irradiance specifically refers to the power of solar radiation hitting a particular surface at any given time. For a given time period 't', the following formula (34) can be used to calculate the solar panel's average hourly output power [6, 30]:

$$P_{PV}^t = \sum_{S=1}^{T_S} Pg_{PVS} * P_s\left(s_g^t\right) \tag{34}$$

Where P^t_{pv} is the solar output, Pgpvs is the amount of solar radiation [6].

The ambient temperature and radiance of the place affect the PV array's output power. PV array power generation is represented by the following equation (35) as a mathematical relation of the amount of solar radiation at the ground level [6,13].

$$Pg_{PVS}\left(sav\right) = N_{Pvmod} * FF * V_S * I_S \tag{35}$$

For a specific radiation level and ambient temperature TA (°C), the following relationships (36-39) can be used to determine the variations in a PV module's current and voltage [13].

$$I_S = \text{ŋ}sv\left[I_{sc} + K_I\left(T_{cS} - 25\right)\right] \tag{36}$$

$$V_S = \left[V_{oc} - K_V * \left(T_{cS}\right)\right] \tag{37}$$

$$T_{cS} = T_A + \text{ŋ}sv S\left(\frac{N_{OT} - 20}{0.8}\right) \tag{38}$$

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{OC} * I_{SC}} \tag{39}$$

The probability of solar irradiance $P_S\left(S^t{}_g\right)$ for each state during any given time period is calculated as (40) [26]:

$$P_S\left(S^t{}_g\right)=\begin{cases}\int_0^{\left(g^t{}_{\dot{s}}+g^t{}_{\dot{s}+1}\right)/2} f^t{}_s(g)ds\, for\, S=1\\ \int_{\left(g^t{}_{\dot{s}-1}+g^t{}_{\dot{s}}\right)/2}^{\left(g^t{}_{\dot{s}}+g^t{}_{g+1}\right)/2} f^t{}_s(g)ds\, for\, S=2\ldots\ldots\left(T_{,s}-1\right)\\ \int_{\left(g^t{}_{\dot{s}-1}+g^t{}_{\dot{s}}\right)/2}^{\infty} f^t{}_s(g)ds\, for\, S=T_{,s}\end{cases} \tag{40}$$

Where N_{pvmod} is the total PV modules, FF is the fill factor, V_s and I_s are the voltage and current at solar irradiance, $g^t{}_s$ is the solar irradiance at s state and t^{th} time, $K_{I\,is}$ the current coefficient (A/°C), $K_{v\,is}$ the voltage coefficient (A/°C), NoT is the cell nominal operating temperature (°C), T_{cs} is the cell temperature (°C), V_{oc} is the no load voltage (V), I_{sc} is the full load current (A), V_{MPP} is the voltage corresponding to maximum power point, I_{MPP} is the current corresponding to maximum power point, and $\mathfrak{m}s\mathcal{v}$ is the mean value of solar irradiance [6].

B. Model for Generating Wind Electricity

With respect to the t^{th} time segment, the power production from WT per hour is represented as [6], and according to WPDF (41) [27]:

$$P^tWT=\sum_{S=1}^{T_{,v}} PG_{WTS}*P_v\left(v^t{}_S\right) \tag{41}$$

For any state at any given time period, the likelihood probability of wind speed P_v (v^t_g) is computed as (42):

$$P_v\left(v^t s\right)=\begin{cases}\int_0^{\frac{\left(v^t{}_{\dot{s}}+v^t{}_{\dot{s}+1}\right)}{2}} f_v^t(v)dv\, for\, S=1\\ \int_{\frac{\left(v^t{}_{\dot{s}-1}+v^t{}_{\dot{s}}\right)}{2}}^{\frac{\left(v^t{}_{\dot{s}}+v^t{}_{\dot{s}+1}\right)}{2}} f_v^t(v)dv\, for\, S=2\ldots\ldots\left(N_v-1\right)\\ \int_{\frac{\left(v^t{}_{\dot{s}-1}+v^t{}_{\dot{s}}\right)}{2}}^{\infty} f_v^t(v)dv\, for\, S=\left(N_v\right)\end{cases} \tag{42}$$

At a speed for state "S," the power output from WT is (43):

$$PG_{WTg}=\begin{cases}0\nu_{aS}\left\langle \nu_{cin}\, or\, \nu_{aS}\right\rangle \nu_{cout}\\ \left(a*\nu^3{}_{aS}+b*P_{rated}\right)\nu_{cin}\le \nu_{aS}\le or\, \nu_N\\ 0\nu_N\le \nu_{aS}\le \nu_{count}\end{cases} \tag{43}$$

Constants *b* and *a* are functions of the nominal wind speed (ν_N) and cut-in wind speed (ν_{cin}), respectively, and are obtained as (45-45) [8]:

$$a=\frac{P_{rated}}{\left(\nu^3{}_N-\nu^3{}_{cin}\right)} \tag{44}$$

$$b=\frac{\nu^3{}_{cin}}{\left(\nu^3{}_N-\nu^3{}_{cin}\right)} \tag{45}$$

Where V_{cout} is the cut-out speed, V_{cin} is the cut-in speed, Prated is the maximum output of wind, and $V_{N\,is}$ the wind speed at nominal conditions [6]

V. GREY WOLF MULTI-OBJECTIVE OPTIMIZATION

In this study, the GW-MOO method is employed to minimize a single objective function to determine the optimal DG capacity. Grey Wolf Optimization was initially innovated by Mirjalili in 2014 [9]. This is founded on the way that grey wolves find food. Typically, grey wolves wander in large groups of five to twelve animals. The wolves are actively hunting as they circle the victim. The mathematical modeling of the encirclement behavior is presented below (46-47) [13].

$$\vec{D}=\left|\vec{C}.\overrightarrow{ж_P}(k)\ -\vec{ж}\ (k)\right| \tag{46}$$

$$\vec{ж}(k+1)=\vec{ж}p(k)\ -\vec{A}.\vec{D} \tag{47}$$

Here, $\vec{C}=2*\vec{r}3$ and $\vec{A}=2*\vec{r}*\vec{r}4-\vec{r}$

Where $\vec{ж}p(k)$ and $\vec{ж}(k)$ are the location vectors of the prey and the wolf, respectively, during the *k*th iteration in which the coefficient vectors are $\vec{A}$ $\vec{C}$. The $\vec{r}$ represents the linear fluctuation in the range [0, 2] with regard to every repetition count, and r3 and r4 represent the random vectors selected between [0, 1].

Wolves lead the hunting process due to their experience in decision-making. The top three solutions understand potential options better, allowing us to prioritize them while adjusting the remaining representatives to align with the top search representative's position. Grey Wolf Optimization is designed for single-objective optimization, relying on a strict hierarchy (alpha, beta, delta wolves). Grey Wolf - Multi Objective Optimization extends GWO for multi-objective problems by integrating Pareto dominance, an external archive, and adaptive leader selection to generate a set of optimal trade-off solutions. Steps to implement GW-MOO [28] for biomass DG capacity optimization with consideration of solar and wind output variability.

Step 1. Data Collection

Gather Data: Gather historical solar radiation, wind speed, and energy generation data from existing farms, along with grid demand data and peak times. Normalize the data for analysis.

Step 2. Statistical Analysis of Renewable Energy Sources

Calculate seasonal averages, standard deviation, and other statistics for solar and wind output, and analyze their correlation to assess their complementary relationship.

Step 3: Define the Optimization Problem With Necessary Constraints

Formulate an objective function that minimizes congestion by (1)-(12).

Step 4. Initialization of the Grey Wolf Optimization Algorithm

Population and Parameters: Establish a population of Grey wolves $\overrightarrow{ж}(k)$ (solutions) at the outset, each of which stands for a possible arrangement of biomass DG capacities at various transmission network nodes. Establish the positions of wolves randomly in the solution space, where each position represents a potential solution $\overrightarrow{ж}(k)$ (placement of biomass DG), the number of iterations, and any other pertinent variables, such as the coefficients α, β, and δ, which are nothing but the best solution, second-best solution, and third-best solution of the capacity of biomass DG, respectively.

Step 5. Fitness Function

Objective: Create a fitness function to evaluate solutions aimed at reducing transmission network congestion, considering voltage stability and power loss. Adjust biomass capacity based on solar and wind forecasts to optimize the objective function.

Constraints: Include restrictions such as power balancing and the voltage limitations found in (4) to (10).

Step 6. Social Hierarchy: Results Obtained After Each Iteration Will Be Considered in Priority As Per Below

Alpha (α) will be the best solution. Then, beta (β) will be the second-best solution. The third-best solution will be delta (δ), and Omega, the remaining wolves, will be the other solutions, i.e., the capacity of biomass DGs about solar and wind output variability.

Step 7. Encircling Prey

Update the positions of wolves based on the positions of α, β, and δ using the encircling behavior equations (48-50):

$$ж_1(k+1) = \overrightarrow{ж\alpha}(k) - A_{\alpha}.\vec{D}\alpha \tag{48}$$

$$ж_2(k+1) = \overrightarrow{ж\beta}(k) - A_{\beta}.\vec{D}\beta \tag{49}$$

$$ж_3(k+1) = \overrightarrow{ж\delta}(k) - A_{\delta}.\vec{D}\delta \tag{50}$$

Where $\overrightarrow{ж\alpha}(k), \overrightarrow{ж\beta}(k), \text{and } \overrightarrow{ж\delta}(k)$ is the position vector of prey, A and C are coefficient vectors (51-53), and

$$\vec{D}\alpha = \overrightarrow{C_1}.\overrightarrow{ж\alpha}(k) - \overrightarrow{ж}(k) \tag{51}$$

$$\vec{D}\beta = \overrightarrow{C_2}.\overrightarrow{ж\beta}(k) - \overrightarrow{ж}(k) \tag{52}$$

$$\vec{D}\delta = \overrightarrow{C_3}.\overrightarrow{ж\delta}(k) - \overrightarrow{ж}(k) \tag{53}$$

Step 8. Hunting

Update the positions of the wolves according to the hunting behavior, considering the influence of the three best solutions (α, β, and δ) :

$$\overrightarrow{ж}(k+1) = \frac{\overrightarrow{ж\ \alpha}\ (k+1) + \overrightarrow{ж\ \beta}\ (k+1) + \overrightarrow{ж\ \delta}\ (k+1)}{3} \tag{54}$$

Where $\overrightarrow{ж\alpha}(k+1)$, $\overrightarrow{ж\beta}(k+1)$, and $\overrightarrow{ж\beta}(k+1)$ are updated positions toward α, β, and δ, respectively.

Step 9. Convergence

Examine convergence using a stopping criterion, such as the fitness function's threshold improvement or the maximum number of iterations. In GWO, no archive, just a simple linear update of the exploration factor. GW-MOO maintains solution diversity and prevents premature convergence.

Step 10. Result

The ideal arrangement of biomass DG capacity in the transmission network is represented by the best solution (α), i.e., after the iterations regarding solar and wind output variability.

Implementation of the GW-MOO flowchart is shown in Fig. 1. Grey Wolf - Multi Objective Optimization is an easy-to-implement optimization method with fewer tuning parameters, making it suitable for real-world applications like DG sizing. It mimics the hunting behavior of Grey wolves, balancing exploration and exploitation to find optimal solutions. The algorithm adjusts its exploration (when the coefficient vector A is outside −1 to 1) and exploitation (when A is between −1 and 1) phases, leading to quick convergence and

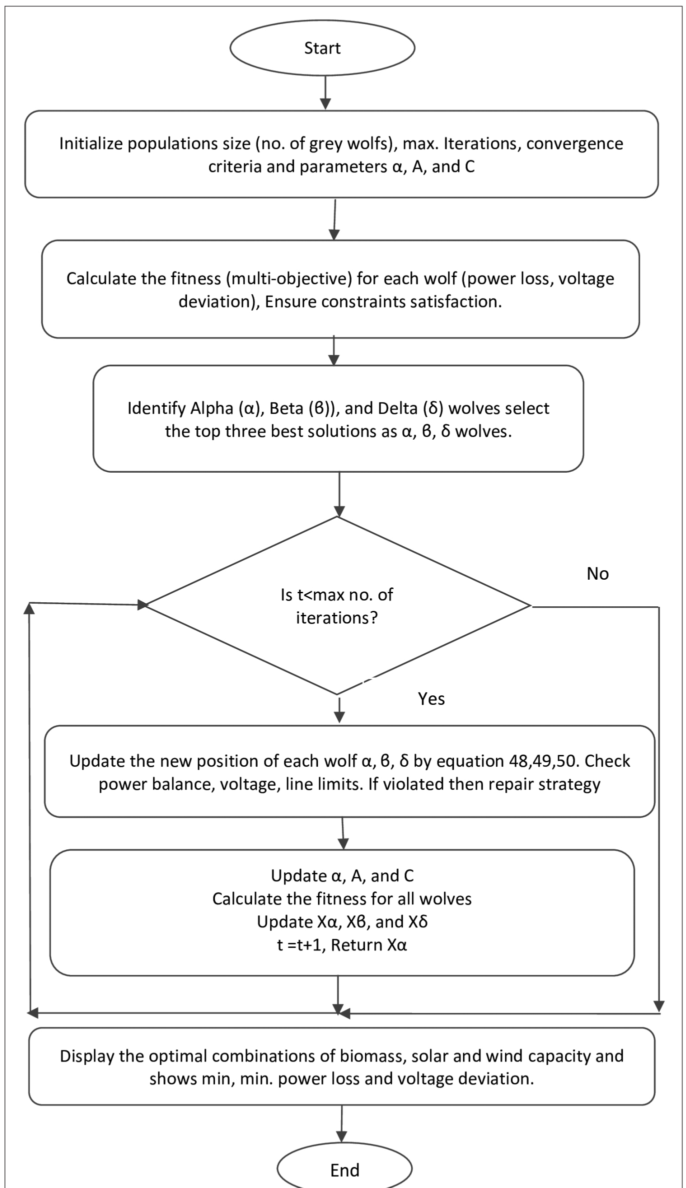

Fig. 1. Flowchart of Grey Wolf - multi objective optimization.

reduced computation time. Grey Wolf - Multi Objective Optimization is versatile, capable of handling complex, nonlinear, or multi-modal objective functions, and is resilient against local optima in DG scaling problems [29]. Below, pseudo-code for GWO-MOO is given [28]:

Initialize the grey wolf population Xi (i = 1, 2, ….n)

Initialize α, A, and C

Calculate the objective values for each search agent

Find the non-dominated solutions and initialize the archive with them

Xα=SelectLeader (archive)

Exclude alpha from the archive temporarily to avoid selecting the same leader

Xβ= SelectLeader (archive)

Temporarily exclude beta from the archive to avoid selecting the same leader

Xδ= SelectLeader (archive)

Add back alpha and beta to the archive

t=1;

while *(t < Max number of iterations)*

for *each search agent*

Update the position of the current search agent by equations (48)-(54)

end for

Update α, A, and C

Calculate the objective values of all search agents

Find the non-dominated solutions

Update the archive with respect to the obtained non-dominated solutions

If *the archive is full*

Run the grid mechanism to omit one of the current archive members

Add the new solution to the archive

end if

If *any of the new added solutions to the archive is located outside the hypercube*

Update the grids to cover the new solution(s)

end if

Xα=SelectLeader (archive)

Exclude alpha from the archive temporarily to avoid selecting the same leader

Xβ= SelectLeader (archive)

Exclude beta from the archive temporarily to avoid selecting the same leader

Xδ= SelectLeader (archive)

Add back alpha and beta to the archive

t=t+1

end while

return ***archive***

In the proposed system, control variables are real power generations of generators and capacities of DGs. Population size is considered 20, and the maximum iterations are 200. The first population of the above variables is generated randomly between lower and upper bounds.

VI. FINDINGS

To reduce network congestion, the integration of BMDGs has been proposed as a novel alternative, considering the intermittent nature of solar and wind DGs to alleviate congestion in the transmission system's network lines. The test system is based on the IEEE 30 bus system [8, 31].

A. Resource Assessment

The Kakdwip region (21.883 N, 88.183 E) experiences unusual seasonal weather variations due to its proximity to the Bay of Bengal and the Tropic of Cancer. The four seasons examined during a year are spring (February to April), winter (November to January), autumn (August to October), and summer (May to July). There are 96 times in a year, divided into 24 segments every season, each of which corresponds to a specific hourly portion of the season [27, 30]. The capacity of biomass-distributed generation is constrained within the range of 0 to 60 MW, representing its operational limits. Solar and wind generation are computed based on practical atmospheric data, with no artificial bounding, as their output is governed by measured solar irradiance and wind speed inputs modeled using Beta and Weibull PDFs, respectively.

Fig. 2 depicts the end product of solar and wind DGs, which was calculated using historical information gathered at the place to determine the mean and standard deviation of solar radiance and wind motion by Tables I and II [8], and Tables III and IV show the specifications of the PV module and wind turbine. Then, a BPDF as well as a WPDF is produced every hour.

B. Creation of Contingencies

In this work, the potency of the suggested MOO-based CM approach is examined by testing it on a standard IEEE 30-bus system [8, 31]. To determine the active powers of the generators, power flows in the lines, and the whole loss in the system, basic OPF is carried out with the aim of minimizing the fuel cost function (2) subject to the constraints (5) to (11). The active power outputs of the different generators, excluding the bus 1 generator, are assumed as the variables for the basic OPF run, in which bus 1 is considered as the reference bus. Table V displays the results of the OPF. The results of GWO have been compared with PSO and FPA algorithms proposed in a recent work. Implementing the GWO outcomes in power costs of 801.8441

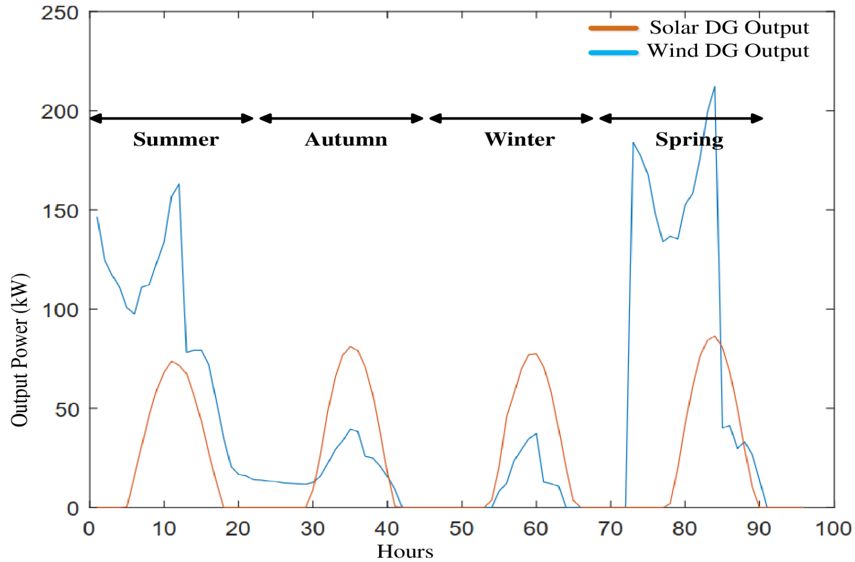

Fig. 2. Results for a randomly chosen location's PV and wind turbine distributed generator outputs.

($/h), which are identical to those of the PSO and FPA techniques, shows its validation. Also, from the base case results, it can be seen that GWO outperforms the other reported algorithms. Further, the convergence curve of PSO and GWO shown in Fig. 3 discloses the speediness of the proposed GWO over the PSO.

Furthermore, the bilateral and multilateral transactions referred from ref. [31] have been incorporated to create a contingency situation in the system. In this work, RPTCDFs are used to allocate the ideal placements for the optimum-sized DGs with respect to the congested line 6–8. Based on the outcomes of the OPF test, the calculated RPTCDFs are displayed in Table VI and are signified graphically in Fig. 4 for each bus. Therefore, it has been determined to insert wind DG and PV DGs on bus number 28 and bus number 29, respectively, as well as biomass DG on bus number 8, in order to reduce congestion in line 6–8. From this perspective, the maximum power output (P_{DG}^{max}) delivered by a renewable distributed generator is limited to 60 MW. The GWO method was used to optimize the proposed objective function, which was first solved by optimizing a single objective before being solved using a multi-objective approach. The power flow through lines 6–8 before optimization was 36.15 MVA, exceeding its thermal limit of 32 MVA and indicating congestion. After the proposed DG placement and dispatch strategy, the flow was reduced to 30.19 MVA, resolving the congestion. This demonstrates the effectiveness of the proposed approach in alleviating line overload.

C. Findings With a Single Objective

In this case, the weight factor is considered as 1 and 0, and vice versa, for each objective during the execution of the programmed algorithm. When a single target is considered, the BM DG capacity and actual losses are calculated with respect to two objectives: voltage deviation and loss minimization. The lower and upper capacity of BM DG and losses for different seasons are obtained by the thought process of the single objectives, respectively, which are given in Tables VII and VIII respectively.

Existing power losses have increased when capacities are changed independently, as seen in Tables VII and VIII. When the losses are augmented separately, the capacities also diverge from their ideal standards, which is shown in Figs. 5 and 6, which indicates that while one of the goals in the CM problem is optimized, the other objective deviates from its optimal standards. As a result, finding an optimal exchange solution between the opposing goals is achievable.

D. Findings With Multi-Objectives

In this case, the weight factor is set at 0.5 for W1 and 0.5 for W2 during the execution of the algorithm, as there are only two objectives in the equation, resulting in equal weightings being assigned. Table IX shows BMDG sizes and Table IX represents losses with multi-objective cases.

It is observed in Table IX as well as through Fig. 6 that the BMDG capacity is less in the summer season, as solar and wind DG output is higher. To manage system congestion, the optimal capacity of BMDG required is less. Fig. 7 shows the LM for autumn, considering both a single objective and multiple objectives for the duration of the day.

Real power losses when taking into account all objectives at once are shown in Fig. 8, and the minimum and maximum values of real losses when taking into account multiple objectives are shown in Table IX. Similarly, in Tables V and VI cover two objectives, namely voltage deviation and loss minimization, showing how the optimal solution changes in both cases if only one target is considered. Therefore, when solving any problem, one needs to take into account several objectives, often known as a Pareto Optima Set. The only difference between the losses for single and multiple objectives over all seasons was that nearly identical results were observed.

Fig. 9 shows the LM for the autumn season when looking at individual objective voltage deviation, loss reduction, and multiple objectives. Overall, the results show that the recommended approach reduces network line congestion more effectively than single-objective approaches for each given problem. The voltages of each bus during congestion and after DGs are added to relieve congestion are displayed in Fig. 10, which indicates that the voltage of congested lines has improved.

TABLE I. MEAN AND STANDARD DEVIATION OF SOLAR IRRADIANCE (KW/M2) IN THE STUDY PERIOD [8]

Hour	Summer		Autumn		Winter		Spring	
	μ_s	σ_s	μ_s	σ_s	μ_s	σ_s	μ_s	σ_s
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0.0032	0.0045	0	0	0	0	0	0
6	0.1278	0.0406	0.0707	0.0299	0.0300	0.0417	0.0158	0.0196
7	0.2538	0.0714	0.2177	0.0433	0.1623	0.0463	0.1605	0.0332
8	0.3824	0.1189	0.3988	0.0803	0.3741	0.0669	0.3412	0.0658
9	0.4908	0.1388	0.5465	0.1121	0.4732	0.0669	0.5060	0.1002
10	0.5680	0.1659	0.6442	0.1336	0.5831	0.0998	0.6385	0.1319
11	0.6164	0.1445	0.6827	0.1492	0.6463	0.1219	0.7120	0.1551
12	0.5990	0.1175	0.6645	0.1452	0.6496	0.1262	0.7305	0.1510
13	0.5614	0.0995	0.5923	0.1282	0.5921	0.1117	0.6780	0.1283
14	0.4672	0.0788	0.4731	0.0999	0.4786	0.0838	0.5699	0.1011
15	0.3548	0.0550	0.3121	0.0635	0.3228	0.0515	0.4124	0.0765
16	0.2228	0.0410	0.1402	0.0309	0.1609	0.0382	0.2394	0.0446
17	0.1030	0.0276	0.0057	0.0112	0.0269	0.0372	0.0834	0.0230
18	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0

Using both single-objective and MOO frameworks, this study examined how to optimize BMDG capacity to minimize power loss and voltage deviation inside an electrical grid. Minimizing voltage variation was the main goal in the single-objective scenario. Table VII illustrates how the enhanced biomass capacity successfully offsets variations in renewable energy sources, resulting in a notable improvement in voltage stability throughout the network.

In addition to improving power supply dependability, lowering voltage deviation also reduced the chance of equipment damage and operational interruptions. Table VII displays somewhat higher loss values. On the other hand, compared to Table VII for the voltage deviation target, Table VIII illustrates how optimization resulted in a discernible reduction in power losses across the network when power loss minimization was taken into account as a single objective. In order to ensure more efficient use of energy, the biomass capacity was calibrated to work in tandem with the solar and wind resources listed in Table VII. This strategy demonstrated the financial advantages of including biomass in the energy mix by resulting in a lower total operating cost.

The trade-offs between voltage deviation and power loss minimization became clear when the research was expanded to a MOO framework, as Table IX demonstrated. A more thorough assessment of the system's performance was made possible by the multi-objective approach, which finally led to the identification of the best biomass capacities that balanced the decrease of both objectives. The findings showed that the MOO provided a synergistic solution that maximized overall system dependability and efficiency, even while notable gains in voltage stability and power loss reduction could be achieved separately.

The results support a multi-objective approach as a better way to improve grid performance, guaranteeing that efficiency and

TABLE II. MEAN AND STANDARD DEVIATION OF WIND SPEED (M/S) IN THE STUDY PERIOD [8]

Hour	Summer		Autumn		Winter		Spring	
	μ_s	σ_s	μ_s	σ_s	μ_s	σ_s	μ_s	σ_s
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0.0032	0.0045	0	0	0	0	0	0
6	0.1278	0.0406	0.0707	0.0299	0.0300	0.0417	0.0158	0.0196
7	0.2538	0.0714	0.2177	0.0433	0.1623	0.0463	0.1605	0.0332
8	0.3824	0.1189	0.3988	0.0803	0.3741	0.0669	0.3412	0.0658
9	0.4908	0.1388	0.5465	0.1121	0.4732	0.0669	0.5060	0.1002
10	0.5680	0.1659	0.6442	0.1336	0.5831	0.0998	0.6385	0.1319
11	0.6164	0.1445	0.6827	0.1492	0.6463	0.1219	0.7120	0.1551
12	0.5990	0.1175	0.6645	0.1452	0.6496	0.1262	0.7305	0.1510
13	0.5614	0.0995	0.5923	0.1282	0.5921	0.1117	0.6780	0.1283
14	0.4672	0.0788	0.4731	0.0999	0.4786	0.0838	0.5699	0.1011
15	0.3548	0.0550	0.3121	0.0635	0.3228	0.0515	0.4124	0.0765
16	0.2228	0.0410	0.1402	0.0309	0.1609	0.0382	0.2394	0.0446
17	0.1030	0.0276	0.0057	0.0112	0.0269	0.0372	0.0834	0.0230
18	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0

TABLE III. SPECIFICATION OF PV MODULE [8]

Parameters	Value
Voltage at maximum power point, VMPP	28.36 V
Voltage at maximum power point, IMPP	7.76 A
Open circuit voltage, V_{oc}	36.96 V
Short circuit current, I_{sc}	8.38 A
Nominal cell operating temperature, NOT	43°C
Current temperature co-efficient	0.00545 A/ °C
Voltage temperature co-efficient	0.1278 V/ °C

reliability objectives are satisfied at the same time. To further improve the robustness of the suggested methods, future research could investigate dynamic optimization strategies and the integration of real-time data.

TABLE IV. SPECIFICATION OF WIND TURBINE

Attribute	Value
Rated output power, P_{rated}	250 kW
Cut-in-speed, v_{cin}	3 m/s
Nominal wind speed, v_N	12 m/s
Cut-out speed, v_{cout}	25 m/s

TABLE V. BASE CASE LOAD FLOW'S FINDINGS

Generator Number	Particle Swarm Optimization (PSO) [30]	Flower Pollination Algorithm (FPA) [30]	Grey Wolf Optimization
G1	176.6624	178.177	176.6482
G2	48.8103	52.905	48.7265
G3	21.4607	23.184	21.5016
G4	21.7339	16.768	21.7097
G5	12.1028	10	12.1788
G6	12.0	12	12.0
F ($/h)	801.8437	802.675	801.8441
Ploss (MW)	9.3510	9.633	9.3648
Megavolt-Ampere (MVA) limit			

VII. CONCLUSIONS

The optimal BMDG capabilities have been taken into account, along with the variable nature of solar and wind DG, to address and solve the problematic CM of transmission. Multiple objectives are considered and merged into a single objective function in order to achieve the optimal sizes of the DGs. The GWO algorithm is utilized to find the ideal DG sizes for integrating into the actual bulk power grid. The IEEE 30-bus is used to observe the strength of the recommended process. Maximum BMDG capabilities for the single voltage deviation objective were determined to be 9.5144 MW in the summer, while the lowest capacities were found to be 9.266 MW in the spring.

In the case of multi-objective maximum BMDG capacities, 9.9533 MW was found in winter, while the minimum is 9.0196 MW in the summer season. Results further indicate that the DG insertion

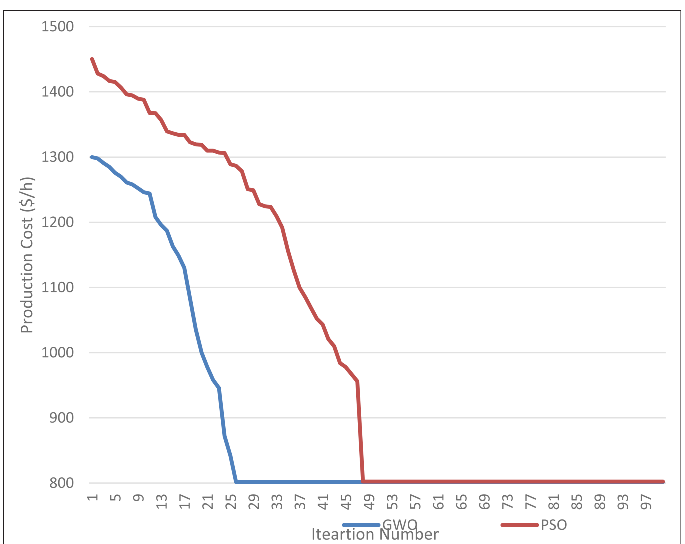

Fig. 3. Base case convergence curve of the Grey Wolf optimization and PSO algorithm.

TABLE VI. REAL POWER TRANSFER CONGESTION DISTRIBUTION FACTOR (RPTCDF)S FOR THE BUSY LINES 6 AND 8

Bus Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
RPTCDFs	0	0.0002	−0.0005	−0.0007	0.0007	0.0012	0.001	−0.8633	−0.0095	−0.015	−0.0095	−0.0117	−0.0117	−0.0137	−0.0172
Bus Number	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
RPTCDFs	−0.0129	−0.0143	−0.0164	−0.0162	−0.0161	−0.0198	−0.0214	−0.0287	−0.0445	−0.1038	−0.1049	−0.1364	−0.1872	−0.1395	−0.1418

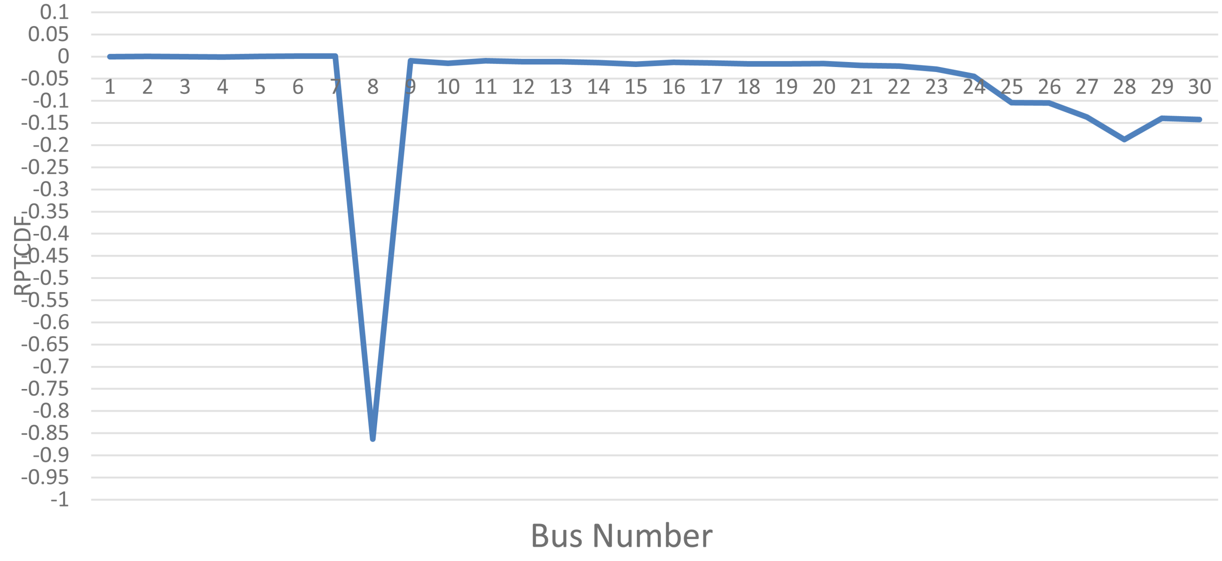

Fig. 4. Value of RPTCDF for 30 buses.

TABLE VII. BIOMASS DISTRIBUTED GENERATOR (MW) CAPACITIES

	Minimizing Voltage Deviations			Minimizing Real Power Losses			
Season	**Minimum**	**Maximum**	**Mean**	**Minimum**	**Maximum**	**Mean**	**FPA [29]**
Summer	9.3846	9.5144	9.8931	57.71	58.29	58.93	UPF = 8.094 09. PF Lag = 8.276
Autumn	9.3848	9.482	9.0157	57.64	58.31	58.94	
Winter	9.3627	9.5169	9.8983	57.65	58.19	58.95	
Spring	9.266	9.4181	9.8883	57.64	58.29	58.97	

TABLE VIII. REAL POWER LOSS (MW)

	Minimizing Voltage Deviations			Minimizing Real Power Losses			FPA [29]
Season	**Minimum**	**Maximum**	**Mean**	**Minimum**	**Maximum**	**Mean**	
Summer	8.5714	9.2081	9.9332	5.9077	6.0117	6.901	UPF = 8.980.9 PF Lag = 9.080
Autumn	8.5068	9.2132	9.8703	5.9079	6.0215	6.9389	
Winter	8.5086	9.1051	9.8496	5.9713	6.0244	7.1019	
Spring	8.6127	9.2026	10.0229	5.9618	6.1237	7.0131	

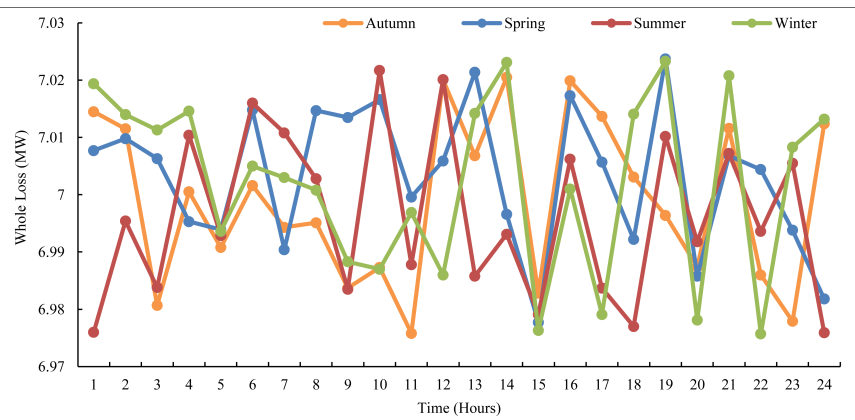

Fig. 5. Total Losses (MW) with distributed generators while losses are considered as an objective during 24 hours are considered.

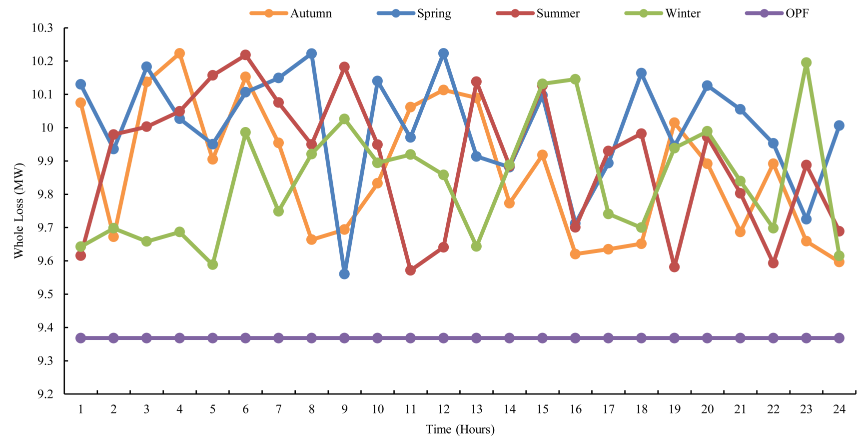

Fig. 6. Whole Losses (MW) with distributed generators, while voltage deviation is considered as an objective during 24 hours are considered.

TABLE IX. BIOMASS DISTRIBUTED GENERATOR CAPACITIES AND REAL POWER LOSSES DURING MULTI – OBJECTIVE OPTIMIZATION

	BM DG (MW) Capacity				Real Power Losses (MW)			FPA [29]
Season	**Minimum**	**Maximum**	**Mean**	**FPA [29]**	**Minimum**	**Maximum**	**Mean**	
Summer	9.0196	9.8003	9.4373	UPF = 8.094 09. PF Lag = 8.276	8.7724	9.2785	9.0041	UPF = 8.98 0.9 PF Lag = 9.080
Autumn	9.1219	9.9021	9.4161		8.6643	9.2961	9.0739	
Winter	9.1106	9.9533	9.4377		8.7058	9.3055	8.9573	
Spring	9.0268	9.0147	9.4076		8.6481	9.3174	8.9521	

enhances the voltage profile and reduces potential power losses. The recommended method is ultimately acknowledged as having successfully reduced congestion and has been quickly applied to real, complex, non-linear optimization issues related to the power scheme. The findings advocate for a multi-objective approach as a more effective strategy for enhancing grid performance compared to a single objective.

This study primarily focused on the GWO for MOO and validated the results by comparing them with a single algorithm from the literature. A broader comparison with multiple metaheuristic algorithms could provide deeper insights into the relative performance of GWO in solving biomass capacity optimization problems. The analysis considered specific system parameters and constraints without incorporating real-time variations in load demand and market dynamics.

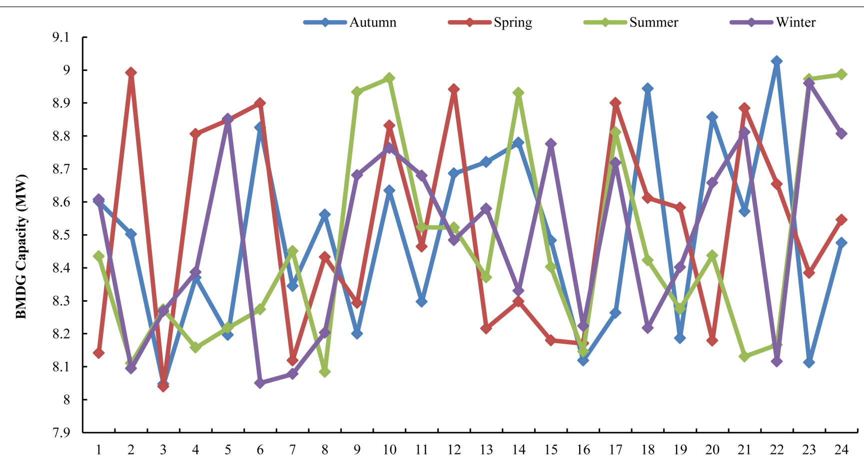

Fig. 7. Biomass distributed generator (MW) capacity when all objectives are considered during a 24-hour period.

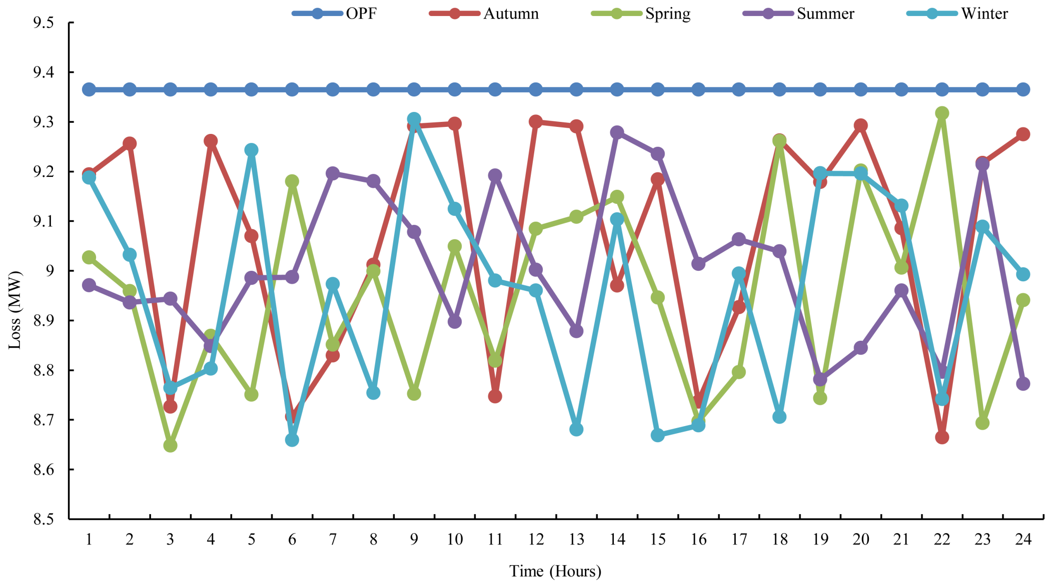

Fig. 8. Losses (MW) when considering all objectives during 24 hours.

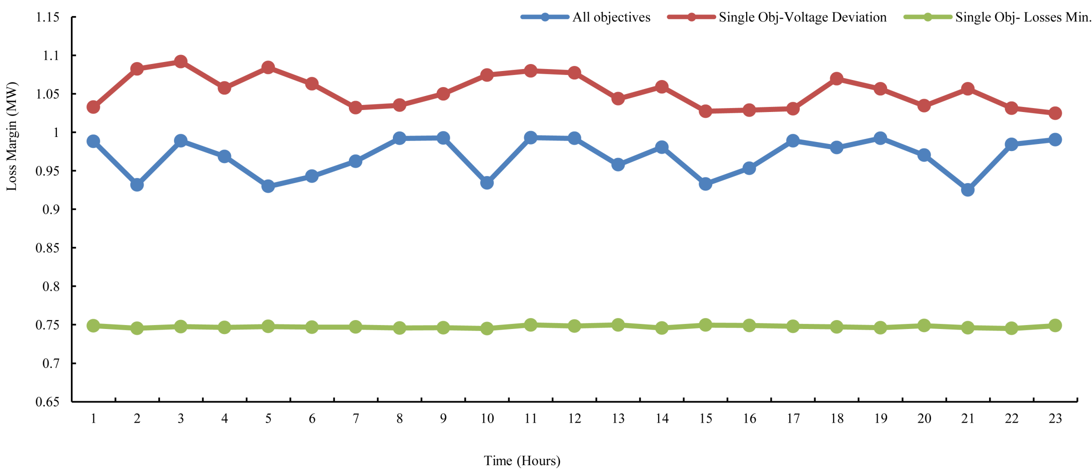

Fig. 9. Loss margin during the autumn season with all and just one goal over a 24-hour period.

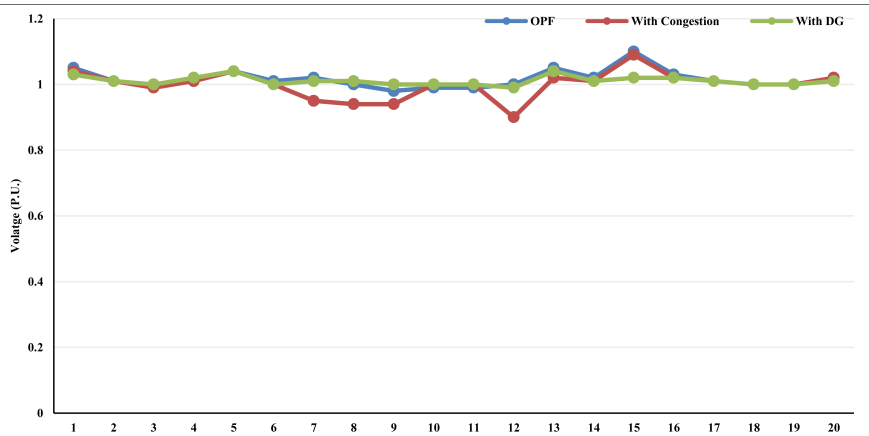

Fig. 10. Voltage at each bus in different conditions.

Future research can extend this work by integrating dynamic system conditions and uncertainty modeling to enhance the robustness of the optimization framework.

NOMENCLATURE

FF	Fill factor
S	State variable
I_{MPP}	Current (A) at the maximum power point
V_{MPP}	Voltage (V) at maximum power point
I_{SC}	Short circuit current (A)
K_V, K_I	Voltage and current temperature co-efficient (V/ °C and A/ °C)
N_s	Number of discrete solar radiance state
N_{Pvmod}	Total number of Photo Voltaic (PV) modules used to form a PV array
N_{OT}	Nominal operating temperature of cell (°C)
ɱ$s\upsilon$	Mean value of solar radiance
g_s^t	State/level of solar radiance at t^{th} time segment
T_{cS}	Cell temperature at S^{th} state (°C)
T_{cg}	Cell temperature at gth state (°C)
T_A	Ambient Temperature (°C)
T_s	Total number of distinct solar radiance states
υ_{cout}	Cut-out wind speed
V_{OC}	Open circuit voltage (V)
P^tWT	Power output of wind turbine
υ_{aS}	Average wind speed
P_{rated}	Highest amount of power that Wind Turbine (WT) can create
$P_{\upsilon}\left(\upsilon^t g\right)$	Weibull probability distribution factor
Pg_{WTS}	Power generation by wind
υ^t_s	Wind speed at time t at S^{th} state
$N_{\mathcal{V}}$	Total number of wind speed states
F_i	Fuel cost of generators
a_i, b_i, c_i	Cost coefficients of i^{th} Generator
P_i	Real power generation i^{th} Generator
N_g	Total number of generators
P^i_S	Generation of power from bus i
P^j_d	Reduced electricity requirement at bus j
P_{rated}	Maximum power that can be generated by WT
P_{gp}^{min}	Minimum actual power output of every generator
P_{gp}^{max}	Maximum actual power output of every generator
$P_S(g_S^t)$	Solar irradiance probability
$RPTCDF_2^K$	–Real transmission congestion distribution factors corresponding to a bus-n and a line-k connected between bus-'P and bus-N
$Ploss^{dg}$	Real power losses after inserting the DG
$Ploss^0$	Real power losses before inserting the DG
P_{PV}^t	Hourly output of solar
Q_{gp}^{min}	Minimum reactive power generation of each generator.
Q_{gp}^{max}	Maximum reactive power generation of each generator.
S_l^{max}	Maximum permissible MVA line flow in line l.
V^{min}	Minimum voltage limits of buses
V^{max}	Maximum voltage limits of buses
δ_i	The voltage angles of i^{th} bus
δ_i^{max}	The maximal limitations of voltage angles of i^{th} bus
δ_i^{min}	The minimal limitations of voltage angles of i^{th} bus
V_{MPP}	Voltage (V) at maximum power point operation
V_i^{DG}	Voltage at the i^{th} node after connecting the DG
V_i^0	Voltage at the i^{th} node before connecting the DG
W_n	n^{th} Weight factor

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

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