

Article

Optimal Power Flow with Stochastic Renewable Energy Using Three Mixture Component Distribution Functions

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Abstract: The growing usage of renewable energy sources, such as solar and wind energy, has increased the electrical system's unpredictability. The stochastic behavior of these sources must be considered to obtain significantly more accurate conclusions in the analysis of power systems. To depict renewable energy systems, the three-component mixture distribution (TCMD) is introduced in this study. The mixture distribution (MD) is created by combining the Weibull and Gamma distributions. The results show that TCMD is better than original distributions in simulating wind speed and solar irradiance by reducing the error between real data and the distribution curve. Additionally, this study examines the optimal power flow (OPF) in electrical networks using the two stochastic models of solar and wind energy. The parameters of the probability distribution function (PDF) are optimized using the Mayfly algorithm (MA), which also solves single- and multi-objective OPF issues. Then, to prove the accuracy of the MA method in solving the OPF problem, single- and multi-objective OPF is applied on a standard IEEE-30 bus system to minimize fuel cost, power loss, thermal unit emissions, and voltage security index (VSI), and results are compared with other metaheuristic methods. The outcomes show that the MA technique is dependable and effective in overseeing this challenging problem. Additionally, the suggested OPF MA-based is studied in the OPF problem while accounting for the uncertainty in the models of the wind and solar systems and taking the emissions, VSI, power loss, and fuel cost into consideration in the objective function. The significance of the work lies in the application of a unique optimization technique to a hybrid electrical system using TCMD stochastic model using actual wind and solar data. The proposed MA method could be valuable to system operators as a decision-making aid when dealing with hybrid power systems.

Keywords: optimal power flow; multi-objective; mixture probability distribution functions; metaheuristic optimization methods; Mayfly algorithm; wind energy; solar energy



Citation: Khamees, A.K.; Abdelaziz, A.Y.; Eskaros, M.R.; Attia, M.A.; Sameh, M.A. Optimal Power Flow with Stochastic Renewable Energy Using Three Mixture Component Distribution Functions. *Sustainability* **2023**, *15*, 334. <https://doi.org/10.3390/su15010334>

Academic Editor: George Kyriakarakos

Received: 9 November 2022

Revised: 7 December 2022

Accepted: 17 December 2022

Published: 25 December 2022



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1. Introduction

Renewable energy sources are increasingly being included in power systems [1]. They occur in a variety of sizes and can be found as dispersed-producing units close to end consumers or as massive central power facilities. To meet a region's load requirements, a hybrid system may be used to integrate several renewable sources, such as wind and solar farms [2]. More reliability and environmental protection are offered by combining multiple renewable resources, such as wind and solar, with backup generators than by employing a single source [3]. Despite being a clean source of energy, renewable energy sources are unreliable and have poor energy density [4]. Researchers are having trouble predicting and controlling the supply of renewable energy [5]. Therefore, accurate forecasting and management of renewable energy systems are essential for guaranteeing a consistent and

trustworthy energy supply [6]. Every location's potential for renewable energy to produce electrical energy is carefully evaluated by examining historical data on wind speed or solar radiation. These records serve as the first step in locating the hybrid energy system. The most crucial factor in a wind system's wind power modeling is wind speed [7,8]. The most important parameter in photovoltaic (PV) generation is solar irradiation [9–11].

Among the most crucial approaches for studying electrical systems is the optimal power flow (OPF) [12]. The primary purpose of OPF is to identify the system's optimum control variables, such as generation power and voltage, which optimize an objective function within the system's constraints. Many control variables are employed in the OPF issue, such as the output power and voltage of the generation unit. The objective functions of the OPF problem used in this study are the cost of generation, emissions of the fuel generators, total power losses, and the Voltage stability indices (VSI) [13,14]. A multi-objective OPF (MO-OPF) is used when two or more objective functions are optimized simultaneously [15–17]. The OPF issue is a significant non-linear non-convex optimization problem with a lot of restrictions. There are several mathematical methods that may be used to tackle this issue. Each of these tactics has the potential to be caught in a local minimum, preventing the algorithm from finding the true optimal solution. These strategies also have downsides because of their substantial computing complexity and time requirements. To address the shortcomings of existing mathematical approaches, metaheuristic algorithms present a novel approach.

The modern Mayfly algorithm (MA) [18] is considered in this work to solve the OPF problem and to estimate the parameters of the wind speed and solar irradiance probability distribution functions (PDFs). Metaheuristic algorithms, such as the MA technique, provide a variety of benefits, including the ability to handle problems with numerous qualitative restrictions and identify the overall optimum solution. The MA technique has a fundamental benefit over other metaheuristic algorithms in that it employs a parameter-free algorithm, meaning that the algorithm parameters have no bearing on the efficiency of the method.

Calculating wind energy and photovoltaic electricity generation depends on forecasting wind speed and solar radiation. Authors used methods for wind speed and sun irradiances include Weibull distribution (WD), gamma distribution (GD), Lognormal distribution (LD), and other PDF types. Numerous original distributions and MDs have been suggested in the literature to simulate wind speed and solar radiation. [19,20]. In contrast to the conventional two-parameter WD, the author in [21] used a three-parameter Weibull distribution, which can replicate wind speed data more precisely. The authors in [21] used a three-parameter WD, which can simulate wind speed data more precisely than the traditional two-parameter WD. The authors in [22] used different combination PDFs to model the distribution of wind frequency, while in [23] WD wind data was utilized instead of real time-series data, and the computed wind energy was found to be exceptionally accurate. Different two and three components mixtures were proposed by Khamees [24] to represent wind speed. Arevalo [25] used LD to mimic solar irradiation and determine the cost of the electrical system's uncertainty. Many researchers employed the OPF problem with conventional fuel generators using metaheuristic strategies [26,27]. Hazra [28] adopted the MO-OPF approach with particle swarm optimization (PSO) to simultaneously minimize two competing objectives: producing cost and emission. Basu [29] applied MO-OPF using differential evolution (DE) to minimize three objective functions simultaneously, while Kumari [30] considered the MO-OPF problem using a genetic algorithm (GA) depending on the strength Pareto method. Khunkitti [31] solved MO-OPF using PSO to minimize fuel cost and power losses emission. Conventional OPF solely considers thermal energy sources but growing fuel prices and environmental impact have prompted governments to investigate renewable energy sources such as wind, solar, and wave energy [32,33]. Wind and solar energy penetration need to be addressed in the electrical system. As to attain the optimal operation for an electrical system with solar and wind energy sources, it is required to include wind generating costs such as penalty and reverse cost into the normal OPF problem, and this issue is called the stochastic optimal power flow (SCOPF) [34]. Shi L [35]

applied the SCOPF problem for a system that includes thermal and wind energy sources based on Weibull PDF. Kathiravan [36] applied the SCOPF problem for a system that includes thermal, wind, and solar energy sources. Khamess [8] proposed a multi-objective SCOPF for a modified IEEE-30 bus system with two wind stations.

In this study, the modeling of renewable energy is presented using novel TCMD. The accuracy of the TCMD is demonstrated by comparing fitting of wind speed and solar irradiance using TCMD to the original WD, LD, and GD. The MA is used to optimize the parameters of original PDFs and TCMDs with root mean square error (RMSE) as an objective function. The results show that the TCMD is better than original distributions, and the best simulation standards are provided by the Weibull–Gamma–Gamma mixture (MWGG). Additionally, the MA optimization strategy resolves the OPF and SCOPF problems. To prove the correctness and validity of the recommended methodology, the standard OPF issue is investigated using the MA technique, and the results are contrasted with those obtained using alternative optimization methodologies. The objective functions taken into account are emissions, VSI, power loss, and fuel cost. Then, single, and multi-objective SCOPF issues are resolved using a modified IEEE-30 bus system with two wind farms and one solar farm. The TCMD is used to simulate the stochastic behavior of wind and solar farms. The cost of dispatching wind energy is divided into two parts: wind energy underestimation and overestimation. The expense of utilizing more reserve capacity is known as the underestimation cost, whereas the cost of the system operator needing to buy more electricity from wind farms than they had anticipated being available is known as the overestimation cost. To illustrate the costs of solar and wind energy, these costs were added to the SCOPF problem. The variation of overestimation and underestimation cost coefficients influences the sharing of the thermal, wind, and solar power generating capacity; this paper explains the reason for variations in power share in numerous scenarios. These scenarios studied the impact of varying the overestimation and underestimation cost coefficients in the values of the optimum costs of fuel, wind, and solar generation, which was examined. This effort also included a study to show the impact of modifying the scheduled wind and solar power on generating costs at various overestimation and underestimation cost coefficient values. This study makes use of five years' worth of data on wind speed and solar irradiation gathered from two sites [37,38].

The novelty of this work can be concluded to the following points:

- Using a novel MA method to estimate parameters of original and mixture distributions;
- Using a novel MA method to solve traditional OPF and SCOPF problems;
- Simulating stochastic behavior and renewable energy using TCMD in the SCOPF problem;
- Using the TCMD model to study the effect of changing scheduled power, renewable sources cost coefficients in the total cost of operation.

2. Renewable Energy Modeling

2.1. Wind Speed and Solar Irradiance Distribution Functions

Three of the most used probability distribution functions, WD, LD, and GD, are shown in Table 1 and are used to estimate solar radiation and wind speed. The newly applied TCMDs are summarized in Table 2, combining WD and GD.

Table 1. Original distribution functions.

Distribution Name	Equation	Distribution Parameters
WD [39].	$isf_w = \frac{k}{c^k} x^{k-1} e^{-(\frac{x}{c})^k}$ (1)	k shape parameter c scale parameter
LD [40].	$f_l = \frac{1}{x\beta\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{\ln x - \alpha}{\beta})^2}$ (2)	α mean β standard deviation
GD [41]	$f_G = \frac{1}{b^a \Gamma(a)} x^{a-1} e^{-\frac{x}{b}}$ (3)	a shape parameter b scale parameter

Table 2. Mixture distribution functions.

Distribution Name	Equation	
Mixture WD	$f_{3w} = w1 * f_{w1} + w2 * f_{w2} + w3 * f_{w3}$	(4)
Mixture WD-WD-GD	$f_{W-W-G} = w1 * f_{w1} + w2 * f_{w2} + w3 * f_G$	(5)
Mixture WD-GD-GD	$f_{W-G-G} = w1 * f_w + w2 * f_{G1} + w3 * f_{G2}$	(6)

where $w1 + w2 + w3 = 1$.

2.2. Wind Power Distribution Function

The following formula can be applied to determine a wind turbine's output power [8]:

$$P_{wind} = \begin{cases} 0 & v \leq v_{c-in} \text{ or } v \geq v_{c-off} \\ \frac{1}{2} \gamma A E_P V^3 & v_{c-in} < v \leq v_{rated} \\ P_r & v_{rated} < v < v_{c-off} \end{cases} \quad (7)$$

where γ is the air density, A is the tower blade area, E_P is the efficiency, v is the wind velocity in m/s, the cut-in speed and cut-off speed are v_{c-in} and v_{c-off} , respectively, v_{rated} is the speed required to reach maximum power, and P_r is the maximum power of a wind generator [42].

2.3. Solar Power Distribution Functions

The output power from PV cells, ignoring the PV cell temperature, can be calculated as follows:

$$P_s(G) = \begin{cases} P_{sr} \left(\frac{G^2}{G_{std} R_c} \right), & \text{for } 0 < G < R_c \\ P_{sr} \left(\frac{G}{G_{std}} \right), & \text{for } G > R_c \end{cases} \quad (8)$$

where G is the solar irradiation in W/m^2 , the standard solar irradiation G_{std} , is $1000 W/m^2$ in a typical setting, irradiation point R_c is defined as $150 W/m^2$, P_{sr} is PV generator's comparable rated power output.

The active power generation from solar PV can be managed using a tracking control technique or charged batteries. As a result, the maximum PV penetration into the system is:

$$P_{s,k} \leq P_{s,k}^{max} \quad (9)$$

where $P_{s,k}$ and $P_{s,k}^{max}$ are the output power and maximum output power from solar cell, respectively.

The Monte Carlo simulation with 8000 samples is used to estimate the renewable energy frequency distribution.

3. Optimal Power Flow

The formulations of the OPF problems are covered in the ensuing subsections.

3.1. Single-Objective OPF Problem

The optimization problem can be formulated as follows:

$$\text{Minimization } f(x) \quad (10)$$

Subjected to:

$$g(x) = 0 \quad (11)$$

$$h(x) \leq 0 \quad (12)$$

where $g(x)$ and $h(x)$ are the equality and inequality constraints, respectively.

3.2. Multi-Objective OPF Problem

Multiple objectives are optimized concurrently in a generic multi-objective optimization problem (MOO). A set of requirements for the optimization problem is specified, and the requirements must be satisfied by the answer. The MOO can be stated this way:

$$\text{Min } f_j(x) \quad j = 1, 2, \dots, Q \quad (13)$$

Subjected to:

$$g_j(x) = 0 \quad j = 1, 2, \dots, K \quad (14)$$

$$h_j(x) \leq 0 \quad j = 1, 2, \dots, L \quad (15)$$

where Q is the number of objectives, K the number of equality requirements, and L the number of inequality constraints.

If the conditions mentioned below are met, the answer x_1 prevails over x_2 : [43]

$$f_j(x_1) \leq f_j(x_2), \quad \forall j \in Q \quad (16)$$

Over the whole search space, the Pareto front solutions are the most common. The i th objective function of a fuzzy membership function can be shown in the following way:

$$\mu_i = \begin{cases} 1 & f_i \leq f_i^{\min} \\ \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}} & f_i^{\min} < f_i < f_i^{\max} \\ 0 & f_i \geq f_i^{\max} \end{cases} \quad (17)$$

The membership function μ^k is calculated as follows for each Pareto front:

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^M \sum_{i=1}^{N_{obj}} \mu_i^k} \quad (18)$$

The optimum compromise solution is the bigger value of μ^k .

3.3. Objective Functions

(a) Fuel Cost

The goal is to lower the thermal generators' running costs C_t (\$/h), and can be formulated as:

$$\text{Min } C_t = \sum_{i=1}^n a_i + b_i p_{gi} + c_i p_{gi}^2 \quad (19)$$

where n is the count of the thermal generators, (a_i, b_i, c_i) are the generator coefficients, and p_{gi} is the output power.

(b) Wind and Solar Generation Cost

The second objective is to lower solar energy cost C_s and wind energy cost C_w (\$/h) and can be formulated as:

$$\text{Min } C_w = C_R + C_P \quad (20)$$

$$\text{Min } C_s = C_R + C_P \quad (21)$$

where C_R and C_P are the reverse and penalty costs, respectively.

When actual renewable energy production falls short of what was anticipated, more energy must be obtained, raising the operational expense known as overestimation cost. The operator will be required to purchase more energy from wind or solar farms they did not anticipate at a fee known as underestimation cost if real available renewable power exceeds the planned quantity [44]. These costs can be computed as the following two equations:

$$C_R = K_R(P_{\text{scheduled}} - P_{\text{available}}) \quad (22)$$

$$C_P = K_P(P_{\text{available}} - P_{\text{scheduled}}) \quad (23)$$

where K_R and K_P are the reverse and penalty cost coefficients, respectively, $P_{\text{available}}$ is the available power by the renewable source, and $P_{\text{scheduled}}$ is the scheduled power.

(c) Active Power Losses

Reduce active power losses is the third goal T_L (MW), and can be formulated as:

$$\text{Min } T_L = \sum_{i=1}^K \sum_{\substack{j=1 \\ i \neq j}}^K R_{ij} \frac{(|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos\delta_{ij})}{|Z_{ij}|^2} \quad (24)$$

where K is the buses count, $|V_i|$ is the absolute value of the voltage, δ_{ij} is the power angle, and R_{ij} and Z_{ij} are the resistance and impedance, respectively.

(d) Voltage Security Index

The fourth objective is to reduce the voltage security index (VSI), and can be formulated as:

$$\text{Min } VSI = \sum_{i=1}^N \left(\frac{|V_i| - V_{\text{avg}}}{dV} \right)^2 \quad (25)$$

$$V_{\text{avg}} = \left(\frac{|V_{\text{max}}| + |V_{\text{min}}|}{2} \right) \quad (26)$$

$$dV = \left(\frac{|V_{\text{max}}| - |V_{\text{min}}|}{2} \right) \quad (27)$$

where $|V_{\text{max}}|$ and $|V_{\text{min}}|$ are the highest and lowest voltage magnitudes, respectively.

(e) Emission Function

The fifth objective is to reduce the emissions E_t (ton/h) of the thermal unit, and can be formulated as:

$$\text{Min } E_t = \sum_{i=1}^n \alpha_i + \beta_i p_{gi} + \gamma_i p_{gi}^2 + \zeta_i \exp(\lambda_i p_{gi}) \quad (28)$$

where α , β , γ , ζ , and λ are the coefficients of thermal units.

(f) Problem constraints

The load flow equations are represented by the equality constraints $g(x)$. It can be stated in the following way:

$$\sum_{j=1}^n p_{gi} = P_{\text{loss}} + P_{\text{load}} \quad (29)$$

$$\sum_{j=1}^n Q_{gi} = Q_{\text{loss}} + Q_{\text{load}} \quad (30)$$

where P_{loss} and Q_{loss} are the losses in the transmission line. P_{load} and Q_{load} are the load power.

The system-operating restrictions are represented by the inequality constraints $h(x)$. they can be stated in the following way:

$$p_{gi\text{min}} \leq p_{gi} \leq p_{gi\text{max}} \quad (31)$$

$$Q_{gi\text{min}} \leq Q_{gi} \leq Q_{gi\text{max}} \quad (32)$$

$$V_{gi\text{min}} \leq V_{gi} \leq V_{gi\text{max}} \quad (33)$$

where Q_{gi} is the reactive power generation.

4. Mayfly Algorithm

Artificial intelligence optimization (AI) methods are one technique to acquire the best solutions [45]. Most of these methods are based on natural behaviors, with a distance requirement for the best solutions being determined by an objective function. The target function you choose has the most influence on the outcome. One of the AI methods is the Mayfly algorithm [18].

The insect family Balaenoptera includes mayflies. Mayflies emerge from their eggs as aquatic nymphs, grow into adults, and then soar to the surface. When mating with a female mayfly, a male mayfly (MMA) dances around a body of water (FMA). The life cycle is continued when the FMAs mate with MMAs in the air and produce offspring/eggs.

The MA can be summarized as follows:

4.1. MMA' Movement

Near a body of water, MMAs gather in swarms. This indicates that they adapt their movement and location to the other mayflies in the swarm. The following is a list of equations that can be used to characterize MMAs:

$$w_i^{t+1} = w_i^t + w_i^{t+1} \quad (34)$$

where w and v are the position and velocity MMAs, respectively.

The MMAs' velocity can be described as:

$$v_i^{t+1} = v_i^t + ae^{-\beta r_p^2} (pbest_i - w_i^t) + be^{-\beta r_g^2} (gbest - w_i^t) \quad (35)$$

where a and b are fixed numbers, the local and global best solutions are $pbest$ and $gbest$, respectively, and r_p and r_g are the separation between the present position and the local and global top positions, respectively.

4.2. FMA' Movement

FMAs travel to the males' area to breed of forming swarms. The following is a list of equations that can be used to characterize FMAs:

$$z_j^{t+1} = z_j^t + u_j^{t+1} \quad (36)$$

where z and u are the FMAs' position and velocity, respectively.

The FMAs' velocity can be described as:

$$u_i^{t+1} = u_i^t + be^{-\beta r_m^2} (w_i^t - z_i^t) \quad (37)$$

where r_m is the distance between FMAs and MMAs.

4.3. Mating

FMAs pick their breeding MMAs in the same manner that they choose their progeny. To develop and generate offspring, the finest MMA partners with the best FMA. The following formulae are used to compute the MA crossover:

$$offspring1 = U \times w_i + (1 - U) \times z_i \quad (38)$$

$$offspring2 = U \times z_i + (1 - U) \times w_i \quad (39)$$

where U is a random number ($0 \leq U \leq 1$).

4.4. Mutation

The offspring are modified, as illustrated in the equation, to prevent the process from being stranded on a local minimum.

$$offspring'_n = offspring_n + ND_{(0,1)} \quad (40)$$

where $ND_{(0,1)}$ is the normal distribution function with $\sigma = 1$ and $\mu = 0$.

The RMSE is selected as objective function in this work, which can be given by:

$$RMSE = \sqrt{\frac{1}{2} \sum_{j=1}^k (y_j - x_j)^2} \quad (41)$$

where k is the classes count, y_i is the real reading from the site, and x_i is the estimated data from the PDF.

The flowchart of MA is shown in Figure 1.

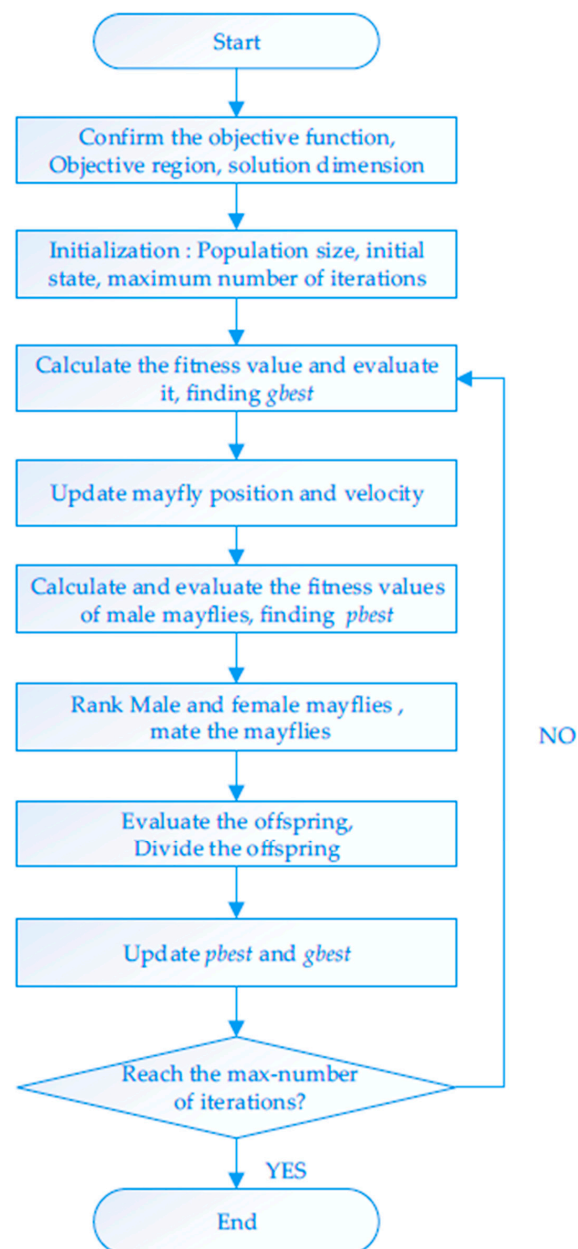


Figure 1. Flowchart of the MA.

5. Results and Discussion

Numerous case studies are included in this paper to demonstrate stochastic modeling of renewable energy. To choose the optimum PDF to represent wind and solar energy, the original and TCMD functions' parameters are first estimated using the MA optimization approach. Then, four scenarios are provided for the study of OPF and SCOPF with single and multiple objectives. The IEEE 30-bus system will be used to address the OPF issue. While the SCOPF will be used in an adjusted IEEE 30-bus system with two wind station in Buses 2 and 5 and one solar farm on Bus 13. The impact of altering the reverse and penalty fees for wind and solar farms on the generation cost will then be demonstrated using two case studies. The impact of adjusting the scheduled power of renewable power on the cost of wind and solar generating will finally be studied through the presentation of one scenario. A software called MATLAB is used to create the MA technique. The Newton–Raphson method was utilized in the MATPOWER software to calculate power flow [46]. The generator's fuel cost and emission coefficients can be found in [8].

5.1. Case 1: Renewable Energy Modeling

In this instance, the MA approach is utilized to calculate the parameters of the original distributions and TCMDs. In the wind speed and solar radiation modeling, respectively, the fitting of the original distributions and TCMDs are shown in Figures 2 and 3. The parameters and RMSE of the original PDFs for wind speed and solar radiation, as well as the recently proposed TCMD functions are summarized in Table 3.

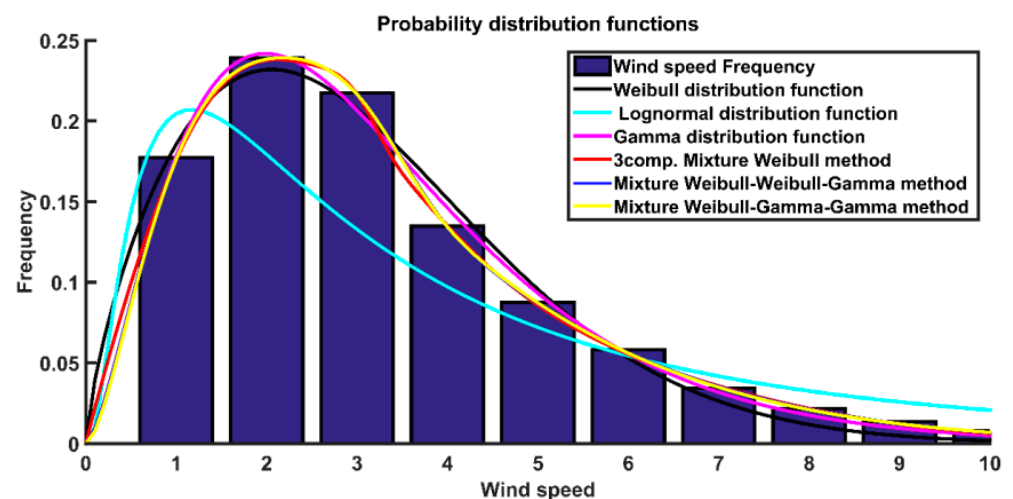


Figure 2. Wind speed modeling.

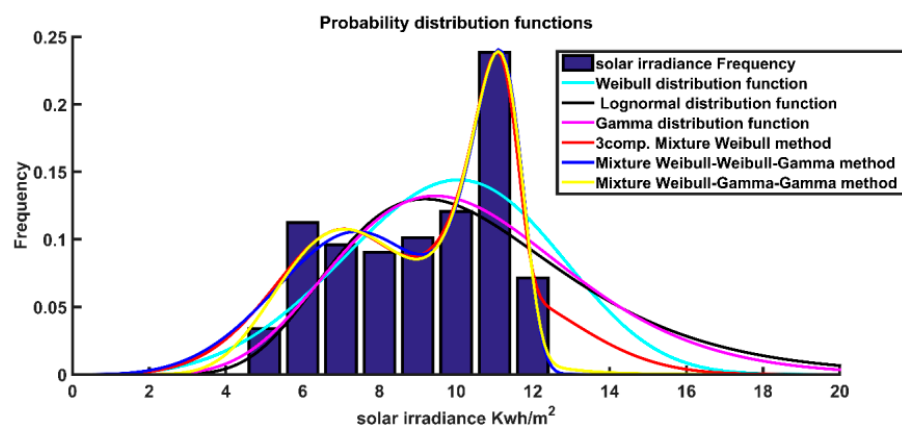


Figure 3. Solar irradiance modeling.

Table 3. Parameters and RMSE for original and mixture PDFs.

Probability Distribution Function	Wind Speed Modeling		Solar Irradiance Modeling	
	Parameters	RMSE	Parameters	RMSE
WD	$k = 1.72$ $c = 3.39$	0.0062	$k = 4.08$ $c = 10.77$	0.046732
LD	$\alpha = 1.15$ $\beta = 1$	0.0249	$\alpha = 2.31$ $\beta = 0.31$	0.052494
LG	$a = 2.60$ $b = 1.23$	0.0038	$a = 10.96$ $b = 0.94$	0.050583
Mixture WD	$C1 = 5.21$ $K1 = 2.14$ $C2 = 2.62$ $K2 = 1.94$ $C3 = 2.94$ $K3 = 10$ $W1 = 0.39$ $W2 = 0.59$	0.00109	$C1 = 6.91$ $K1 = 5.13$ $C2 = 10.75$ $K2 = 4.13$ $C3 = 11.11$ $K3 = 20$ $W1 = 0.24$ $W2 = 0.5$	0.013409
Mixture WD-WD-GD	$C1 = 5.33$ $K1 = 2.01$ $C2 = 3.03$ $K2 = 5.24$ $a = 2.72$ $b = 1$ $W1 = 0.27$ $W2 = 0.05$	0.000736	$C1 = 11.18$ $K1 = 17.03$ $C2 = 7.80$ $K2 = 4.33$ $a = 15.43$ $b = 17.26$ $W1 = 0.412$ $W2 = 0.5$	0.014118
Mixture WD-GD-GD	$C1 = 3.02$ $K1 = 5.27$ $a1 = 5.62$ $b1 = 1$ $a2 = 2.74$ $b2 = 1$ $W1 = 0.05$ $W2 = 0.19$	0.00068	$C = 11.16$ $K = 17.07$ $a1 = 15.63$ $b1 = 0.482$ $a2 = 15.46$ $b2 = 8.34$ $W1 = 0.394$ $W2 = 0.498$	0.012515

The results show that, due to their reduced RMSE, TCMDs fit wind and solar irradiance data more closely than the original distribution. The MWGG has the least RMSE, with values of 0.0006 in wind speed modeling and 0.012 in solar irradiance modeling. In comparison to GD for wind speed modeling, the RMSE dropped by 71%, and to WD for solar irradiance, by 73%.

5.2. Case 2: Optimal Power Flow

Using the MA technique, four single-objective OPFs are used to reduce thermal generation cost, power loss, emissions, and VSI in the standard IEEE 30-bus framework. The convergence curves for the four objective functions are shown in Figure 4. Table 4 displays the values of the objective functions and the optimal control variables for the four single-objective OPF issues. To prove the validation and accuracy of the proposed MA method the optimal values of the four objective functions are compared with other methods from the literature in Tables 5 and 6. The results show that the MA method has the best results compared to other metaheuristic methods and proves the accuracy of the proposed MA method.

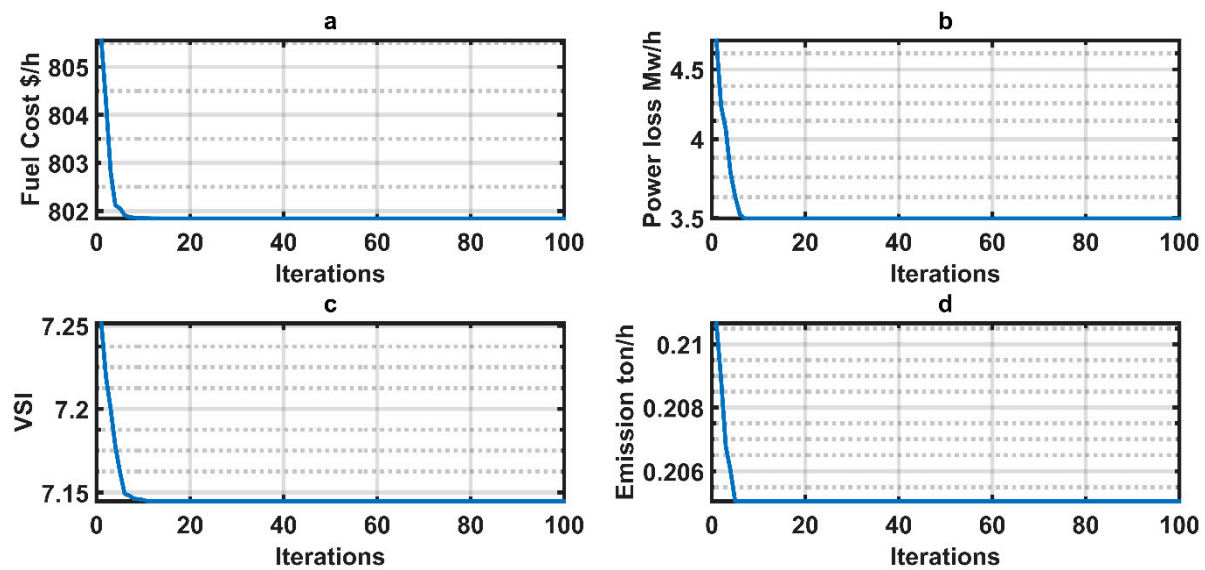


Figure 4. Convergence curves for OPF problem.

Table 4. Optimal control variables and results for OPF problem.

Objective Function	Fuel Cost (\$/h)	Power Loss (MW)	VSI	Emission (ton/h)
P_{G1}	176.7	51.9	177.5	64.3
P_{G2}	48.8	80	20	67.7
P_{G5}	21.5	50	15	50
P_{G8}	21.6	30	10	35
P_{G11}	12	35	30	30
P_{G13}	12	40	40	40
Fuel Cost	801.8	968.6	849.9	945.5
Power Loss	9.4	3.5	9.1	3.6
VSI	7.6	7.2	7.1	7.2
Emission	0.4	0.2	0.4	0.2

Table 5. Comparison of emissions, power loss, and VSI.

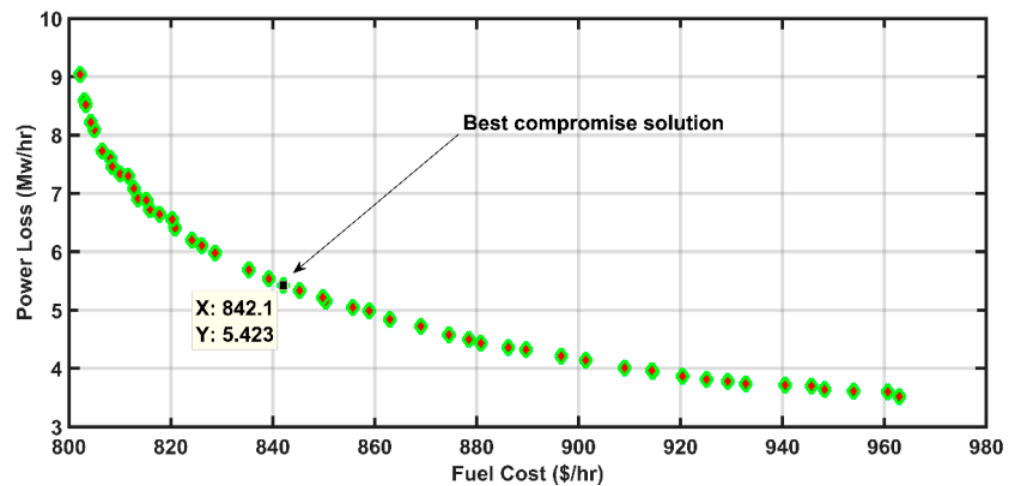
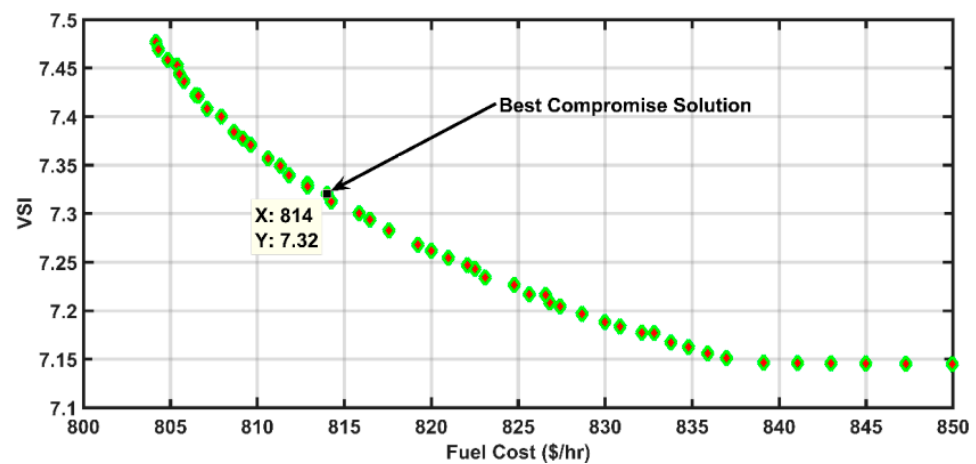
Technique	Emissions Minimization (\$/h)
MA	0.2050
GA [47]	0.20723
PSO [47]	0.2063
Improved PSO [47]	0.2058
Technique	Power Loss minimization (MW/h)
MA	3.49
Harmony search algorithm [48]	3.51
GA [30]	3.62
Technique	VSI minimization
MA	7.1449
DE [49]	8.2367
GWO [49]	8.268

Table 6. Comparison of fuel cost.

Method	Fuel Cost Minimization (\$/h)
MA	801.84
Gray wolf optimizer (GWO) [50]	801.86
DE [51]	802.39
GA [52]	801.96
Shuffled frog leaping algorithm [53]	802.51

5.3. Case 3: Multi-Objective Optimal Power Flow

For the standard IEEE 30-bus framework, three MO-OPF scenarios are studied to minimize fuel cost with power loss, VSI, and emission utilizing the MA technique. The Pareto front solutions for the three cases and the corresponding compromise solution are shown in Figures 5–7. Table 7 shows the compromise solution for each scenario with the corresponding power generation.

**Figure 5.** Pareto front for fuel cost and power loss.**Figure 6.** Pareto front for fuel cost and VSI.

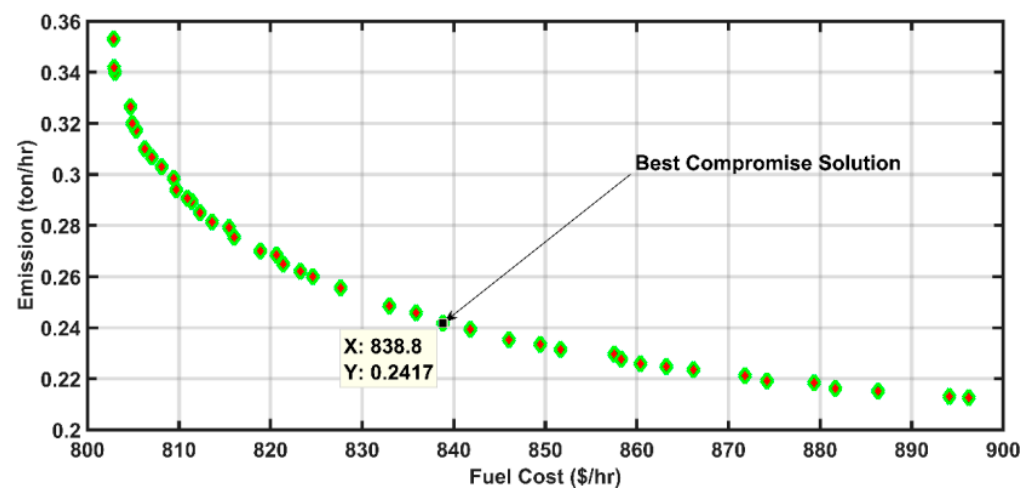


Figure 7. Pareto front for fuel cost and emission.

Table 7. Optimal values of compromise solutions.

Objective Functions	Fuel Cost-Power Loss	Fuel Cost-VSI	Fuel Cost-Emission
P_{G1}	112.49	163.50	112.61
P_{G2}	56.36	46.47	58.67
P_{G5}	33.41	19.42	29.23
P_{G8}	34.43	11.00	34.73
P_{G11}	27.66	24.81	25.85
P_{G13}	24.47	26.80	27.94
Fuel Cost	842.06	814.25	838.81
Power Loss	5.42	8.59	5.64
VSI	7.36	7.33	7.34
Emission	0.24	0.33	0.24

5.4. Case 4: Stochastic Optimal Power Flow

To achieve optimal planned wind and solar power, the MA technique is employed to solve SCOPF in the modified IEEE-30 bus framework. Generators two and five of the standard system were converted into wind stations with a maximum capacity of 80 MW and 50 MW. Moreover, Generator 13 was converted into a solar farm with a rated capacity of 40 MW. Minimization of overall cost, power loss, VSI, and emission are the SCOPF goal functions in this case study. The MWGG is used to simulate wind and solar energy as it has the best simulation characteristics as indicated in Case 1. The reserve cost coefficient K_R is selected equal four for wind farms and 20 for the solar farm and the penalty cost coefficient K_P is selected equal to one for wind farms and 1.5 for solar farm. Table 8 shows the optimal control variables and scheduled power by wind and solar farms and the corresponding values of the objective functions for the four single-objective SCOPF problems. The convergence curves for the four objective functions are shown in Figure 8.

Table 8. Optimal control variables and results for SCOPF problem.

Objective Function	Total Cost (\$/h)	Power Loss (MW)	VSI	Emission (ton/h)
P_{G1}	51.90	51.90	200.00	51.90
$P_{scheduled2}$	80.00	80.00	0.00	80.00
$P_{scheduled5}$	50.00	50.00	0.00	50.00
P_{G8}	35.00	35.00	10.00	35.00
P_{G11}	30.00	30.00	30.00	30.00
$P_{scheduled13}$	40.00	40.00	40.00	40.00

Table 8. Cont.

Objective Function	Total Cost (\$/h)	Power Loss (MW)	VSI	Emission (ton/h)
Fuel cost	370.07	350.31	2226.29	350.31
Wind Power Cost	289.87	319.95	48.79	321.54
Solar Power Cost	32.03	122.89	123.12	124.48
Total Cost	691.96	793.15	2398.20	796.33
Power Loss	6.40	3.50	11.90	3.50
VSI	7.46	7.21	7.14	7.21
Emission	0.17	0.11	0.33	0.11

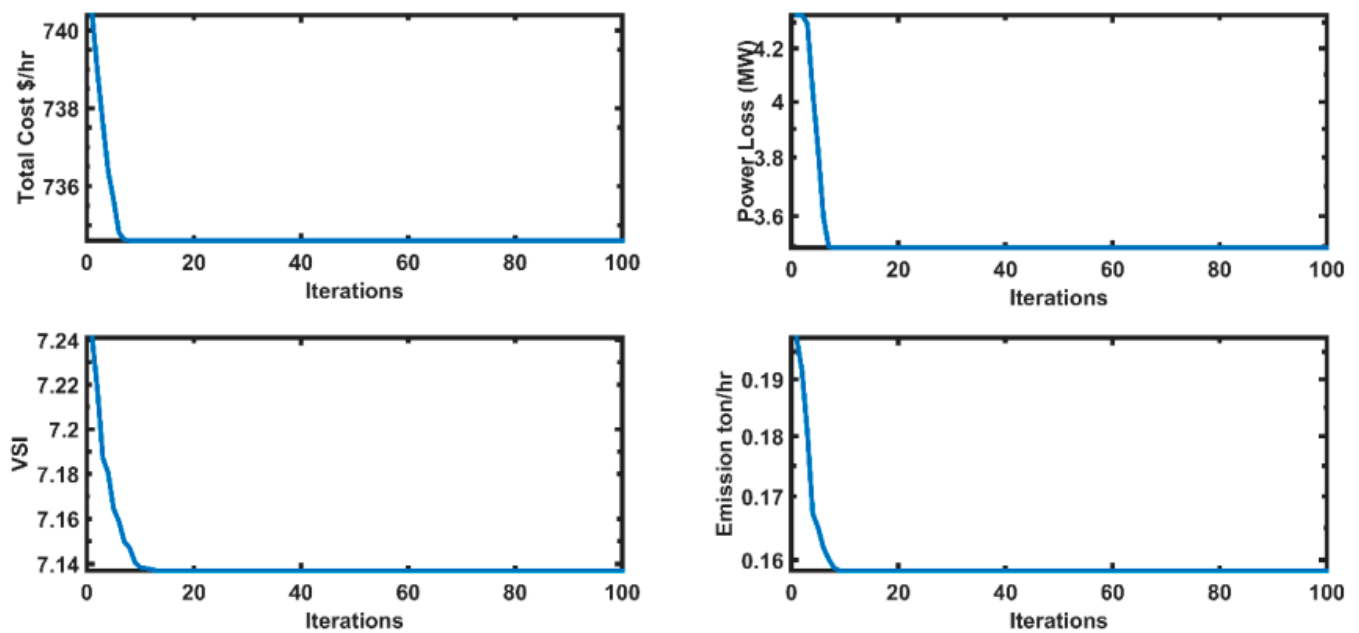


Figure 8. Convergence curves for SCOPF problem.

5.5. Case 5: Multi-Objective SCOPF

With the same power system used in last case, three MO-OPF scenarios are considered to minimize total cost with power loss, VSI, and emission utilizing the MA technique. The Pareto front for the three cases and the corresponding compromise solution are shown in Figures 9–11. Table 9 shows the compromise solution for each scenario with the corresponding optimal power generation and scheduled power for renewable sources.

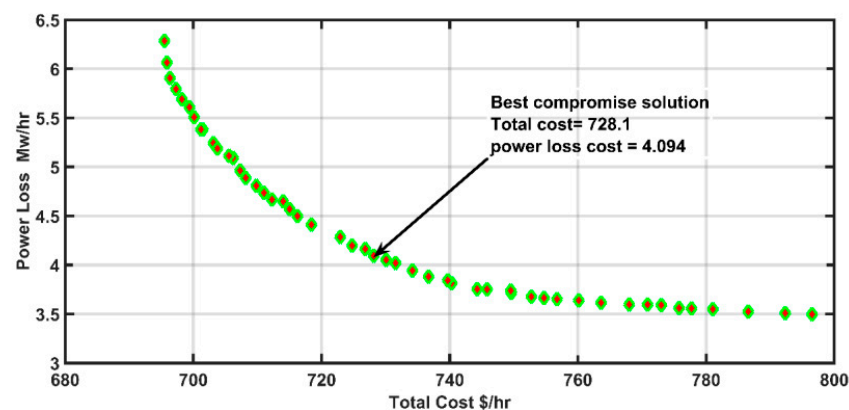


Figure 9. Pareto front for total cost and power loss.

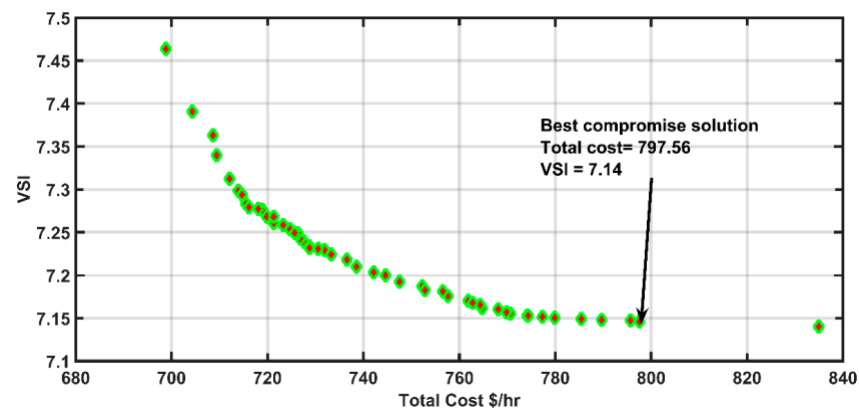


Figure 10. Pareto front for total cost and VSI.

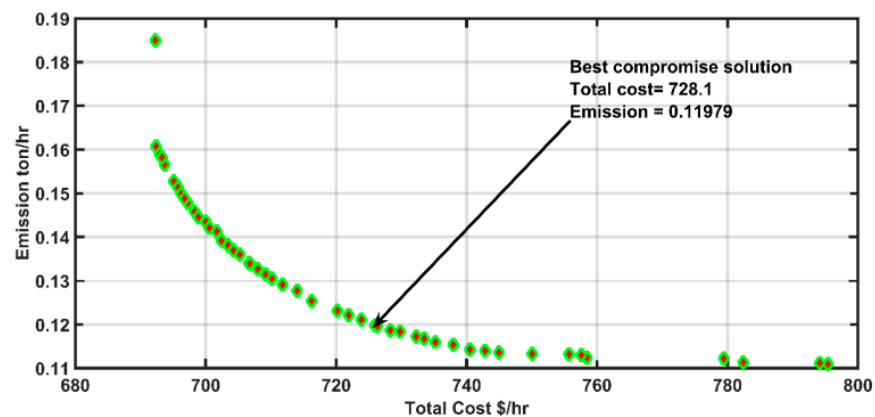


Figure 11. Pareto front for total cost and emission.

Table 9. Optimal values of compromise solutions.

Objective Functions	Total Cost-Power Loss	Total Cost-VSI	Total Cost-Emission
P_{G1}	74.33	133.90	76.49
$P_{scheduled2}$	79.94	70.63	79.99
$P_{scheduled5}$	49.99	6.97	49.99
P_{G8}	35.00	10.00	30.33
P_{G11}	23.32	30.00	26.53
$P_{scheduled13}$	24.92	40.00	24.23
Fuel cost	376.86	480.85	378.33
Wind Power Cost	317.85	195.04	322.75
Solar Power Cost	28.46	124.44	26.12
Total Cost	728.17	797.56	728.20
Power Loss	4.09	8.09	4.17
VSI	7.41	7.15	7.38
Emission	0.12	0.18	0.12

5.6. Case 6: Wind and Solar Generation Costs versus Penalty Cost Coefficient

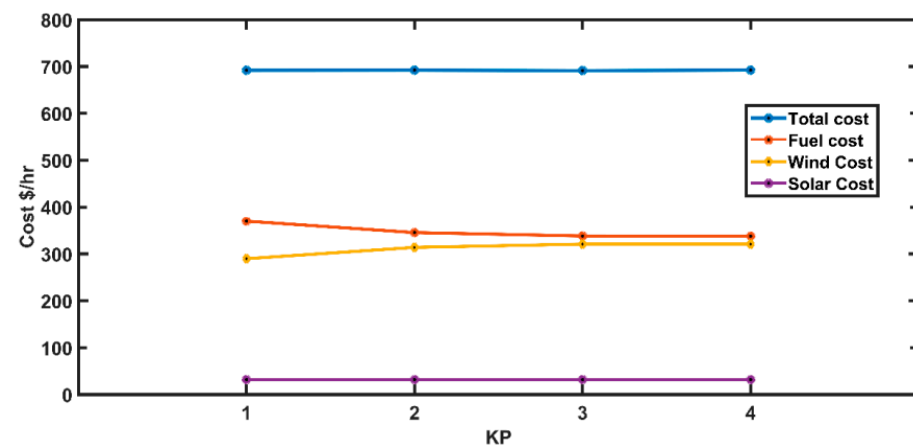
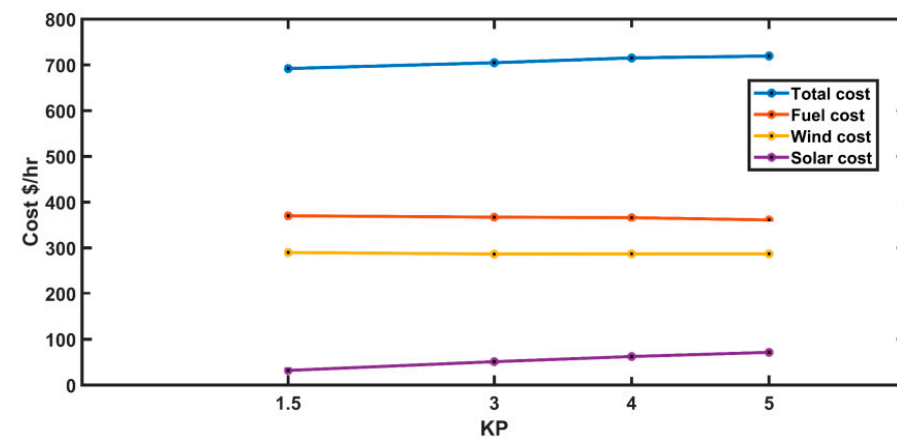
The MWGG is used to simulate wind and solar energy with the same parameters evaluated in Case 1 and with the same values of reverse cost in Case four. The penalty cost coefficient changed from 1 to 4 for the wind farms and from 1.5 to 5 for solar farm. Tables 10 and 11 show the effect of changing the penalty cost of the wind and solar farms, respectively, on the generation cost. Figures 12 and 13 show the variation of generation cost against the penalty cost coefficients of wind and solar farms, respectively. When K_P rises, overall generating costs fluctuate very slightly, while planned electricity from wind and solar farms remains constant at rated power.

Table 10. Wind farm penalty cost versus generation cost.

K_P	1	2	3	4
Fuel Cost	370.07	345.60	338.37	338.18
Wind Power Cost	289.87	314.26	321.07	321.53
Solar Power Cost	32.03	32.32	31.99	32.62
Total Cost	691.96	692.18	691.43	692.34

Table 11. Solar farm penalty cost versus generation cost.

K_P	1.5	3	4	5
Fuel cost	370.07	367.13	366.01	360.98
Wind Power Cost	289.87	286.48	286.81	286.84
Solar Power Cost	32.03	51.13	62.42	71.56
Total Cost	691.96	704.74	715.24	719.38

**Figure 12.** Variation of total cost vs. penalty cost of wind stations.**Figure 13.** Variation of total cost vs. penalty cost of solar stations.

5.7. Case 7: Wind and Solar Generation Costs versus Reserve Cost Coefficient

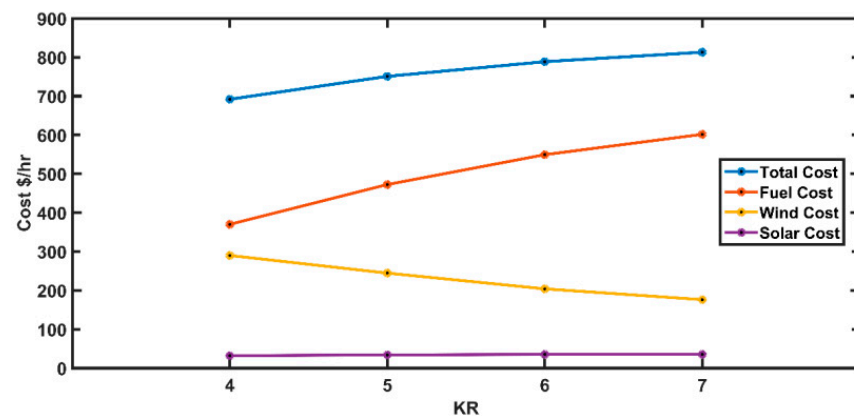
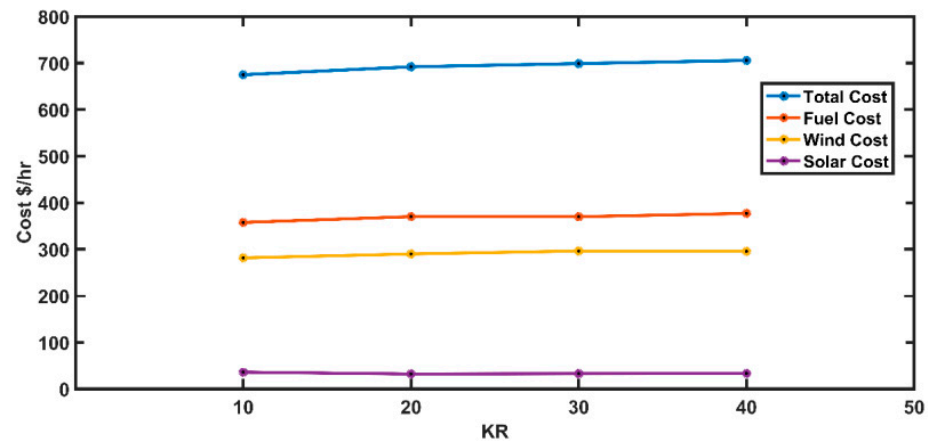
The reverse cost coefficient changed from four to seven for the wind farms and from 10 to 40 for solar farms. Tables 12 and 13 show the effect of changing the reverse cost of the wind and solar farms, respectively, on the generation cost. Figures 14 and 15 show the variation of total cost and penalty cost coefficient for wind and solar farms, respectively. It can be seen that, the optimal planned power from wind and solar farms is reduced as K_R grows, as the drop in scheduled power necessitates less spinning reserve.

Table 12. Wind farm reverse cost versus generation cost.

K_R	4	5	6	7
Fuel Cost	370.07	472.45	549.32	601.65
Wind Power Cost	289.87	244.50	204.00	176.15
Solar Power Cost	32.03	33.95	35.34	35.26
Total Cost	691.96	750.89	788.66	813.06

Table 13. Solar farm reverse cost versus generation cost.

K_R	10	20	30	40
Fuel cost	357.59	370.07	369.89	377.04
Wind Power Cost	281.46	289.87	296.25	295.37
Solar Power Cost	35.88	32.03	32.75	33.26
Total Cost	674.92	691.96	698.89	705.67

**Figure 14.** Variation of total cost versus reverse cost of wind farms.**Figure 15.** Variation of total cost versus reverse cost of solar farms.

5.8. Case 8: Wind and Solar Generation Cost versus Scheduled Power by the Operator

The scheduled wind power for G_2 , G_5 , and G_{13} vary from 0 to 80 MW, 0 to 50 MW, and 0 to 40 MW, respectively. Figures 16 and 17 display the cost of wind power as it varies with planned power. Figure 18 shows the variation of solar power cost versus scheduled power. The results show that the cost of overestimation rises as scheduled power rises, but the cost of underestimating falls as scheduled power rises.

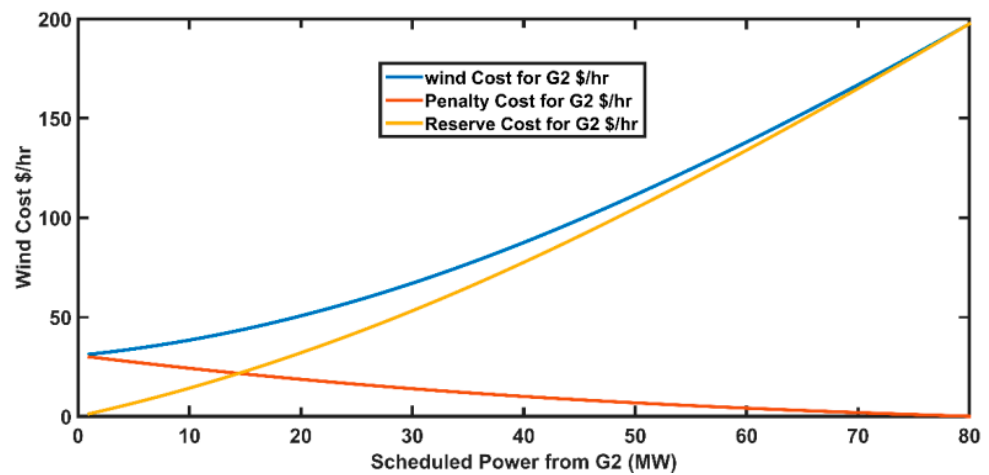


Figure 16. Cost of wind power against scheduled power for G2.

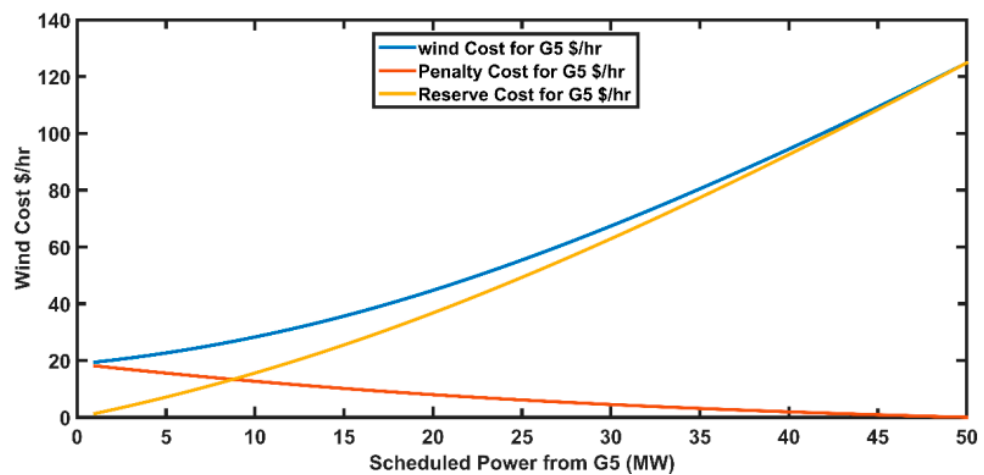


Figure 17. Cost of wind power against scheduled power for G5.

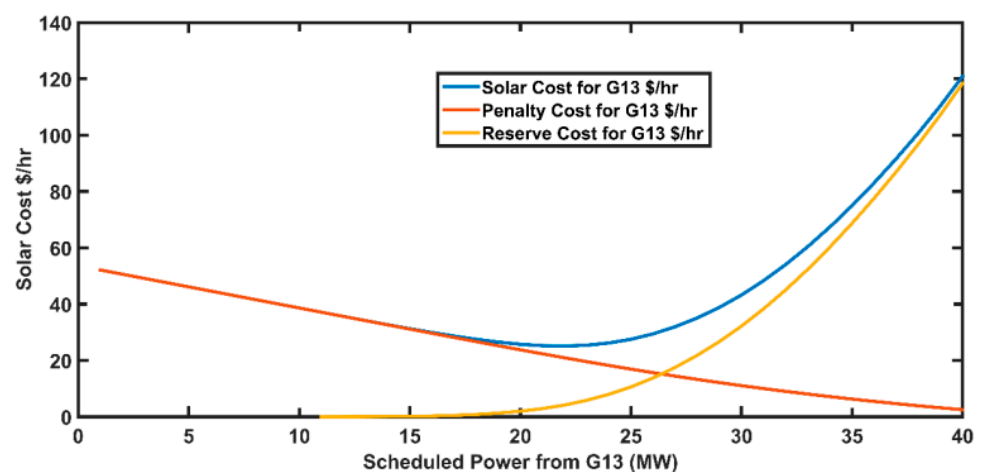


Figure 18. Cost of solar power against scheduled power for G13.

6. Conclusions

This research recommends the use of TCMDs to improve the precision of the most widely used PDFs that are used to describe wind speed and solar irradiance frequency distribution. Three TCMDs, which mix WD and GD, are employed in this study. The novel metaheuristic MA approach is used to calculate the distribution function's parameters.

The MWGG offers the most accurate simulation criteria for both wind speed and solar radiation modeling. The RMSE is decreased by 71% and 73% for the solar irradiation and wind speed, respectively, when comparing the MWGG to the best original PDF. The MA approach is then used to solve the OPF and MO-OPF challenges to reduce generating costs, power losses, VSI, and emissions. On typical IEEE-30 bus systems, the performance of the proposed method was assessed, and the outcomes were compared to those obtained using various optimization techniques. The outcomes revealed that the MA approach generated the best outcomes, proving its accuracy and validity. On a modified IEEE-30 bus framework, the SCOPF is also resolved using the MA approach. Using numerous case studies, this article demonstrates the best wind and solar farm scheduling power. It can be concluded that the MA strategy outperformed previous metaheuristic methods while solving OPF problems with consideration for wind and solar energy penetration and PDF parameters. Additionally, it performed better at determining the SCOPF's ideal wind and sun schedule.

Author Contributions: A.K.K. and M.A.A. designed the problem under study, performed the simulations and obtained the results; M.R.E. analyzed the obtained results. A.K.K. and M.A.S. authored the paper, which was further reviewed by A.Y.A. and M.A.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received a fund from Future University in Egypt (FUE).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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