Water Cycle Optimization for Economic Dispatch in Microgrids with Uncertainty Considerations

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Abstract: Microgrids serve as pivotal frameworks for the seamless integration of diverse energy assets, including combined heat and power (CHP) plants, distributed energy storage systems, and renewable energy resources (RERs). The incorporation of CHP plants within microgrid architectures facilitates the proficient exploitation of both electrical and thermal energy, concurrently mitigating greenhouse gas emissions. The inherent intermittency of RERs, particularly wind energy, when compounded by dynamic load fluctuations, exacerbates uncertainties, thereby influencing the stability and efficiency of the system. To optimize cogeneration scheduling amid RER uncertainties, a scenario-based probabilistic framework with WCOA is employed for resource dispatch. WCOA excels in handling wind power variability and load fluctuations, achieving a 23.73% cost reduction compared to conventional methods, enhancing microgrid efficiency and flexibility.

Keywords: Cogenerating plant, Microgrid, Water cycle algorithm, Economic dispatch, Scenario based generation, Renewable Energy Resources, Uncertainty modelling.

1. Introduction

A microgrid is a network of interconnected loads and dispersed resources so as to can function as an amalgamated system as associated to the focal grid or activate autonomously in islanded mode. Microgrids encompass gained prominence owing to their consistency and steadiness, especially when included with disseminated energy storage, renewable resources and CHP system, enabling cost effective process, lower emissions, and reduced transmission losses. CHP-enabled microgrids further enhance flexibility and quality, particularly during grid outages, making them an essential component of modern energy systems. CHP units are valued for their ability to simultaneously generate electricity and thermal energy by utilizing waste heat, improving overall efficiency and reducing thermal energy costs. However, integrating RERs introduces uncertainties that necessitate comprehensive analysis to maintain system stability [1]. Wind power integration in CHP plants is inhibited by its dependency on heat and electricity demand, complicating optimization. Studies [2] indicate that wind penetration is highest when forecasted wind and load patterns align.

Microgrid adoption [3] is increasing due to its role in reinforcing traditional power systems. The integration of RERs, CHP units, and energy storage enhances cost efficiency and reliability. Various optimization techniques have been applied to the CHP dispatch issue, together with real-coded genetic algorithms [4], grey wolf optimization (GWOA) [5], oppositional teaching-learning-based optimization [6], squirrel search optimization (SSOA) [7], gravitational search algorithm [8], exchange market algorithm [9], Harris hawk optimization (HHOA) [10], group search algorithm [11], and modified particle swarm optimization (PSO) [12].

Despite wind power's emission-free benefits, its variability poses dispatch challenges. Heat storage systems mitigate this by decoupling CHP units' thermal and electrical constraints. Chance-constrained optimization for economic dispatch is explored in [2, 13], while multi-objective dynamic economic and environmental dispatch models account for wind and load uncertainties in [14, 15]. Scenario-based uncertainty modeling using a roulette wheel approach is presented in [16]. PSO and enhanced PSO optimize fuel cost and emissions, while the multi-objective water cycle algorithm (MOWCA) [17] determines optimal RER placement. The point estimate method (PEM) models RER uncertainties, and hybrid optimization techniques, including heap-based and jellyfish search algorithms [18], improve CHP economic dispatch by balancing power and heat demand while minimizing fuel costs.

Economic dispatch in CHP-integrated microgrids faces challenges from wind intermittency and load fluctuations. Traditional deterministic models fail to address renewable energy variability, leading to suboptimal scheduling and increased costs. The dynamic nature of these uncertainties demands advanced optimization frameworks incorporating probabilistic programming, scenario analysis, and adaptive control strategies to enhance dispatch efficiency and grid reliability.

Based on an extensive literature survey on economic dispatch in CHP systems, several critical research gaps have been identified and categorized below with certain recommendation for the existing system.

1.1 **Handling Uncertainties:** Current methodologies often struggle to effectively manage uncertainties linked to variable clean sources and fluctuating load demands in CHP systems. Advanced optimization techniques capable of real-time adjustment to these uncertainties are needed.

1.2 **Integration of Advanced Algorithms:** While some studies use conventional optimization methods, there's a notable absence of advanced algorithms like metaheuristics or probabilistic programming for optimizing economic dispatch in CHP systems. These could offer enhanced flexibility and accuracy in scheduling decisions.

1.3 **Optimization of Multi-Objective Functions:** Many studies prioritize cost minimization without adequately addressing objectives such as emissions reduction, system reliability, or operational flexibility. Developing multi-objective optimization frameworks specific to CHP systems is essential to balance economic, environmental, and operational goals.

Addressing these gaps is crucial for advancing economic dispatch in CHP systems, facilitating their integration with renewable energy sources, enhancing operational efficiency, and ensuring grid reliability in dynamic energy landscapes. This study employs the WCOA algorithm [19-20] to solve the probability-based dynamic economic dispatch (PBDED) problem. With minimal user-defined parameters, WCOA efficiently handles a broad spectrum of optimization challenges while maintaining robust exploitation and exploration abilities, making it well-suited for large-scale problems.

The essential aid of this work includes:

- The study pioneers the use of WCOA for multi-objective CHP-enabled microgrid dispatch, marking its first implementation in this domain.
- A probabilistic optimization model is developed to account for uncertainties in load demand and wind variability, ensuring compliance with heat and power balance constraints. The performance of WCOA is evaluated against PSO for comparative analysis.
- The goal of the proposed study is to fill in the gaps found in earlier research, such as the heuristic and meta-heuristic technique's limited application to smaller dimensions and their vulnerability to local optimum solutions.
- A large number of constraints and choice factors are involved in the calculation of economic dispatch, which increases computing time and system complexity. Comparing WCOA to other approaches, however, reveals a solution with lower computational time.

In CHP systems, economic dispatch necessitates optimizing energy generation while managing uncertainties from renewable energy variability and fluctuating demand. CHP units enhance efficiency by co-generating heat and power but face challenges in balancing cost, reliability, and sustainability. Advanced optimization techniques are crucial for uncertainty management, improved wind energy integration, and enhanced economic and operational efficiency.

This study advances optimization methods for PBDED by applying WCOA within a possible paradigm that accounts for uncertainties and incorporates heat-power balancing, non-convex generator characteristics, and valve point loading effects, yielding more precise economic dispatch solutions for CHP-integrated microgrids.

The paper is structured as follows: Section 2 details the problem formulation, microgrid modeling, objective function formulation, and uncertainty modeling. Section 3 describes the system; Section 4 outlines the WCOA methodology for CHP microgrid optimization. Section 5 presents and analyzes the results. Section 6 concludes by summarizing key findings and contributions. This structured approach ensures a comprehensive study of CHP-enabled microgrid dispatch, from structure modeling to optimization and consequences.

2. Problem Formulation

In the PBDED issue for a CHP-based microgrid, the goal is to determine the optimum dispatch approach for each generator per hour and scenario, minimizing generation costs while adhering to constraints. The integration of wind energy introduces variability due to uncertainty, impacting the economic dispatch process. It aims to allocate resources efficiently, minimizing operational expenses while meeting electrical and thermal load demands within safe operational bounds, ensuring reliable and sustainable microgrid performance.

2.1 Objective Function

The desired function of the PBDED problem [19] is expressed in Eq. (1), while the cost functions for power, cogeneration, and heat-only units are outlined in Eq. (2), (3), and (4), respectively.

$$\mathrm{PBDED_{OF}} = \sum_{S=1}^{N_S} P_S \sum_{T=1}^{24}\left(\sum_{I=1}^{N_P} C_I(P_{I,T,S}^{P}) + \sum_{J=1}^{N_C} C_J\left(P_{J,T,S}^{C}, H_{J,T,S}^{C}\right) + \sum_{K=1}^{N_H} C_K\left(P_{K,T,S}^{H}\right)\right) \quad (1)$$

$$C_I\left(P_{I,T,S}^{P}\right) = \alpha_I (P_{I,T,S}^{P})^2 + \beta_I P_{I,T,S}^{P} + \gamma_I + \left|\delta_I \operatorname{Sin}(\varepsilon_I(P_I^{P,min} - P_{I,T,S}^{P}))\right| \ (\$/h) \quad (2)$$

$$C_J\left(P_{J,T,S}^{C}, H_{J,T,S}^{C}\right) = a_J (P_{J,T,S}^{C})^2 + b_J P_{J,T,S}^{C} + c_J + d_J\left(H_{J,T,S}^{C}\right)^2 + e_J H_{J,T,S}^{C} + f_J P_{J,T,S}^{C}, H_{J,T,S}^{C} \ (\$/h) \quad (3)$$

$$C_K\left(H_{K,T,S}^{H}\right) = A_K (H_{K,T,S}^{H})^2 + B_K H_{K,T,S}^{H} + C_K (\$/h) \quad (4)$$

$C_I(P_I^P)$ is the price of generation, for the I[th] power-only unit and it is generating P_I^P MW of electric power. The generation cost of J[th] cogenerating units for generating P_J^C MW electrical power and H_J^C MWth heat power is shown by $C_J\left(P_{J,T,S}^{C}, H_{J,T,S}^{C}\right)$. $C_K\left(P_K^H\right)$ is the price of generation of the heat-only unit while producing H_H^K MWth heat power. N_P, N_C, and N_H are used to denote the numbers of power-only, cogenerating and heat-only units, respectively.

The impartial limitation for electrical and heat requirement balance criteria in the PBDED is shown by Eq. (5) and (6).

$$\sum_{I=1}^{N_P} P_{I,T,S}^{P} + \sum_{J=1}^{N_C} P_{J,T,S}^{C} = P_{D,T,S} \quad (5)$$

$$\sum_{J=1}^{N_C} H_{J,T,S}^{C} + \sum_{K=1}^{N_H} H_{K,T,S}^{H} = H_{D,T,S} \quad (6)$$

$P_{D,T,S}$ and $H_{D,T,S}$ represents the electrical load and heat power demands at time T in scenario S, respectively. The power and heat demand are 200 MW and 115 MW respectively.

The price functions for power-only and heat-only units are presumed to be linear, as defined in Eq. (7) and Eq. (8). The possible thermo-electric effective region of the cogeneration plant is illustrated in Figs. 1 and 2, respectively.

$$C_1(P_1) = 50\ P_1;\ 0 \le P_1 \le 150 \quad (7)$$

$$C_4(H_4) = 23.4\ H_4;\ 0 \le H_4 \le 2695.2 \quad (8)$$

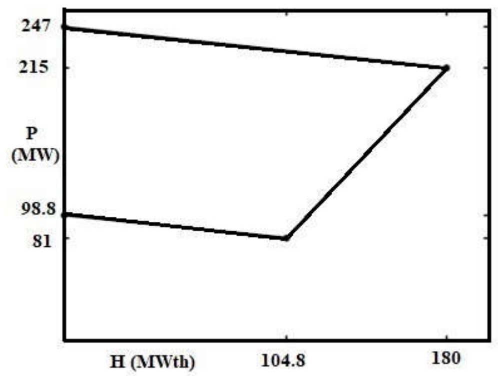

Figure 1: Operable region of unit 5

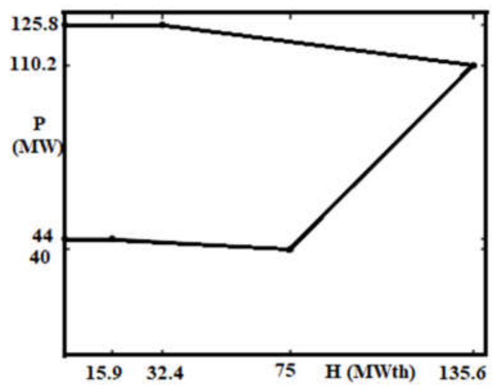

Figure 2: Operable region of unit 6

The production of each electrical and thermal unit must remain within the specified bounds, as outlined in Eq. (9) to Eq. (12).

$$P_I^{P,min} \leq P_{I,T,S}^{P} \leq P_I^{P,max} \tag{9}$$

$$\mathrm{P_J^{C,min}}\left(\mathrm{H_J^C}\right) \leq \mathrm{P_{J,T,S}^{C}} \leq \mathrm{P_J^{C,max}}(\mathrm{H_J^C}) \tag{10}$$

$$\mathrm{H_J^{C,min}}\left(\mathrm{P_J^C}\right) \leq \mathrm{H_{J,T,S}^{C}} \leq \mathrm{H_J^{C,max}}\left(\mathrm{P_J^C}\right) \tag{11}$$

$$\mathrm{H_K^{H,min}} \leq \mathrm{H_{K,T,S}^{H}} \leq \mathrm{H_K^{H,max}} \tag{12}$$

$\mathrm{P_I^{P,min}}$ and $\mathrm{P_I^{P,max}}$ are correspondingly the lesser in addition to higher bounds for the electrical productivity of power only units, $\mathrm{P_J^{C,min}}$ and $\mathrm{P_J^{C,max}}$ denotes the lesser and higher electric power output and $\mathrm{H_J^{C,min}}$ and $\mathrm{H_J^{C,max}}$ represent the obligated for the heat yield of cogenerating units. The variety for heat production in heat-only units are indicated by $\mathrm{H_K^{H,min}}$ and $\mathrm{H_K^{H,max}}$.

The power produced by a wind turbine is a task of its present wind speed and the description of the wind turbine, and it is urbanized as given in Eq. (13).

$$P_{W,T}^{F} = \begin{cases} 0 & V_T < V^{CL}, V_T < V^{CL} \\ P^{max} \times \left(\frac{V_T - V_{CL}}{V_R - V_{CL}}\right) & V^{CL} \leq V_T < V^{R} \\ P^{max} & V^{R} \leq V_T \leq V^{CO} \end{cases} \tag{13}$$

$\mathrm{P_{W,T}^{F}}$ denotes the output of wind turbine at time T.$\mathrm{V^{CO}}$, $\mathrm{V^{CL}}$, and $\mathrm{V^{R}}$ represents the wind turbines cut-off speed, cut-in speed, and rated speed. $\mathrm{P^{max}}$and $\mathrm{V_T}$ are the turbine's maximum yield power and the wind velocity forecast for time T.

2.2 Uncertainty modeling of wind power and load demand

In microgrid setting up, anticipating electrical requirement is complex due to inbuilt uncertainties influenced by climatic conditions, hourly price variations, and individual consumption patterns [22, 23]. Similarly, wind power generation introduces variability, driven by location and weather conditions. To mold these reservations, a set-up-based approach is utilized, involving scenario creation and reduction. The roulette wheel process, as outlined in [21], assigns probabilities to different scenarios, ensuring a representative set of possible outcomes.

This approach enables the scheduling algorithm to account for uncertainties, facilitating optimized decision-making and a robust assessment of system performance under diverse conditions.

$$W_{P,T,S} = W_{P,T,Forecasted} + \Delta W_{P,T,S}; \quad T = 1, \ldots, 24; \; S = 1, \ldots, N_S \tag{14}$$

$$L_{D,T,S} = L_{D,T,Forecasted} + \Delta L_{D,T,S}; \quad T = 1, \ldots, 24; \; S = 1, \ldots, N_S \tag{15}$$

$W_{P,T,S}$ and $L_{D,T,S}$ denote the wind power and load stipulate at time T in scenario S, while $W_{P,T,Forecasted}$ and $L_{D,T,Forecasted}$ are the forecasted represents. The forecast errors, $\Delta W_{P,T,S}$ and $\Delta L_{D,T,S}$, correspond to deviations at time T in scenario S. The total number of scenarios is denoted by N_S. The probability density function of each arbitrates associated with wind power and load requires must be separated, as illustrated in Fig. 3. The seven periods in Fig. 3 are symmetrically centered on zero, each with a width equivalent to the forecast error standard deviation (σ), set at 10% of the forecasted value.

The probability of each given interval at time T is expressed as $a_{I,T}$; I = 1,….,7. The outline of growing probabilities of known intervals is 1.

$$\sum_{I=1}^{7}(a_{I,T}) = 1; \tag{16}$$

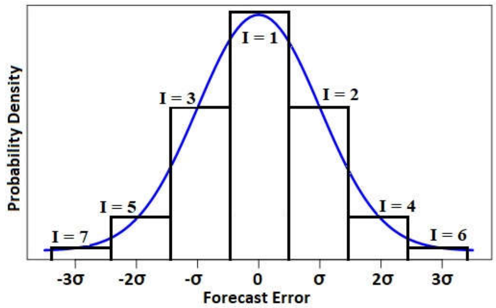

Figure 3: Probability Density Function

In this process a set of plausible scenarios are created that represent different possible outcomes or states of uncertainty. In the context of wind power and load demand uncertainties, scenario generation would typically involve considering factors such as historical data, weather forecasts, and other relevant parameters to simulate a range of potential future conditions. For each setting, a twofold vector is constructed to define the binary elements of wind power and load requirement. This is achieved by producing a random number within 0, 1 and sequentially examining it with the collective probabilities of planned intervals, starting from the last. The first interval with a cumulative probability equal to or exceeding the generated number is selected, setting its analogous binary limitation to 1. This binary vector encapsulates the precise wind power and load requirement configuration for the scenario, enabling the generation of diverse scenarios that probabilistically capture uncertainty and variability, as formulated in Eq. (17).

$$\text{Scenario (S)} = \left[BP_{1,T,S}^{WP}, \ldots\ldots, BP_{7,T,S}^{WP}, BP_{1,T,S}^{LD}, \ldots\ldots, BP_{7,T,S}^{LD}\right]; T = 1, \ldots\ldots, 24 \quad (17)$$

$BP_{I,T,S}^{WP}$ and $BP_{I,T,S}^{LD}$ stands for binary specifications for the known spaces at time T in scenario S for the wind power and load requirement correspondingly. The likelihood of the scenes is resolute as depicted in Eq. 18.

$$P_S = \frac{\prod_{T=1}^{24}(\sum_{I=1}^{7}(BP_{I,T,S}^{WP} \times a_{I,T}) \times \sum_{J=1}^{7}(BP_{J,T,S}^{LD} \times b_{J,T}))}{\sum_{S=1}^{N_S}(\prod_{T=1}^{24}((\sum_{I=1}^{7}(BP_{I,T,S}^{WP} \times a_{I,T}) \times \sum_{J=1}^{7}(BP_{J,T,S}^{LD} \times b_{J,T})))} \quad (18)$$

P_S indicates the scenario prospect. $a_{I,T}$ and $b_{J,T}$ are the personal probabilities of wind power and load requirements for periods I and J and at time T. The challenge accurately model wind power and load demand reservations is addressed through scenario reduction techniques, as recommended in the literature [24-27]. The objective is to retain a representative subset of scenarios while minimizing redundancy to ensure computational tractability. However, the methodology for scenario reduction whether statistical, optimization based, or criteria driven needs clarification.

This study employs the fast forward algorithm for scenario reduction, following these steps:

1. Compute the pair wise distance between generated scenarios.
2. Determine the regular distance of each scenario to each and every others and select the scenario with the minimum space first.
3. Identify the scenario with the minimum distance to the selected set and iteratively update the selection.
4. Reassign the probability of unselected scenarios to their nearest selected counterparts.

Using this method, 1000 scenarios were reduced to 10, balancing uncertainty representation with computational feasibility. This trade-off improves the sturdiness and consistency of optimization results.

3. System Description

A CHP plant, or cogeneration facility, concurrently produces electricity and practical heat from a solitary energy resource. It employs heat revival systems and a gas turbine, steam turbine, or IC machine, to generate mechanical energy, which is then transformed into electricity via a alternator. As an autonomous dispersed production system, it is typically situated close to the consumption point. Comprising multiple integrated components, a CHP system efficiently delivers both heat and electricity for various applications. Fig. 4 illustrates its typical layout.

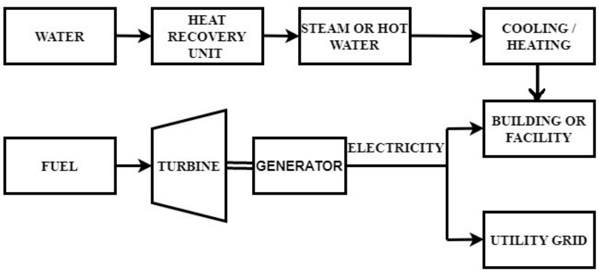

Figure 4: Schematic of CHP power plant

3.1 CHP empowered microgrid

Fig. 5 illustrates the structure of a CHP-faciliated microgrid, adapted from [21], comprising four power units, two cogeneration units, one heat-only unit, and 55 wind turbines (2 MW each). The valve-point loading effect is incorporated to account for generator operating characteristics, introducing nonlinear and non-smooth fuel cost behavior. Fig. 6 presents a schematic of the integrated power and heating networks, interconnected via coupling components, such as CHP units, which enable energy exchange between the systems. These units simultaneously generate electricity and recover waste heat for district heating. To enhance cost function accuracy, the valve-point loading effect is considered. Forecasted electricity and heat demand values, sourced from [10], range between 600 MW and 150 MWth, respectively.

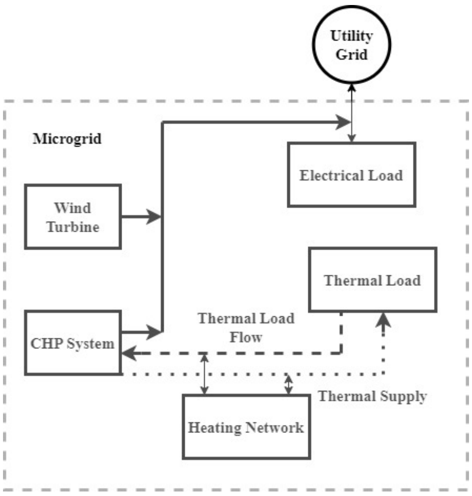

Figure 5: CHP enabled microgrid

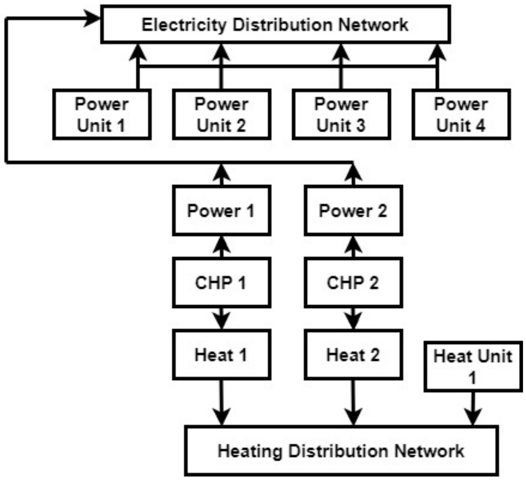

Figure 6: Power and Heat Network

The cost parameters for power-only, cogeneration, heat-only units, and wind turbines are listed in Tables 1–4. The power unit cost parameters are α, β, γ, δ and ε while CHP and heat-only unit coefficients are given as a, b, c, d, e, f and A, B, C, respectively.

Table 1: Cost parameters of power units [21]

P_G Unit	α	β	γ	δ	ε	P^{min}	P^{max}
1	0.0080	2.0	25.0	100.0	0.0420	10.0	75.0
2	0.0030	1.80	60.0	140.0	0.040	20.0	125.0
3	0.00120	2.10	100.0	160.0	0.0380	30.0	175.0
4	0.0010	2.00	120.0	180.0	0.0370	40.0	250.0

Table 2: Cost coefficients of cogenerating units [21]

PG Unit	a	b	c	d	e	f
5	0.03450	14.50	2650.0	0.030	4.20	0.0310
6	0.04350	36.00	1250.0	0.0270	0.60	0.0110

Table 3: Cost coefficients of thermal units [21]

P_G Unit	A	B	C	H^{min}	H^{max}
7	0.0380	2.01090	950.0	0	2695.20

Table 4: Wind turbines parameters [21]

Rated Power (MW)	Cut-in Speed (m/s)	Rated Speed (m/s)	Cut-Off Speed (m/s)
2.0	3.0	13.0	25.0

4. Optimization Methodology

The Water Cycle Optimization Algorithm (WCOA) is introduced as a environment stimulated method for solving constrained optimization in cogeneration plants, modeled on the movement of water from streams and rivers into the sea [19-20]. The algorithm initializes a random population, analogous to precipitation, and evaluates individuals based on cost function values. The best solution, termed the sea, represents the optimal individual, while beneficial solutions (rivers) guide the remaining population (streams) toward convergence. This iterative process refines solutions over time. The complete methodology is detailed in [26], with Fig. 7 illustrating the algorithm's flow.

The main steps include:

1. Defining parameters (N_P, N_{SR}, D_{max}, and maximum number of iterations).
2. Mapping power and heat generation outputs as decision variables, initializing them within limits, and structuring the population into streams, rivers, and the sea.
$$\mathrm{Population_T} = \begin{bmatrix} \text{Sea River}_1,\ \text{Sea River}_2,\ \text{Sea River}_3 \\ \text{Stream } N_{SR} + 1, \text{Stream } N_{SR} + 2, \text{Stream } N_{SR} + 3 \\ \text{Stream } N_P \end{bmatrix} \quad (19)$$
$$N_{SR} = \text{Number of Rivers} + 1 \quad (20)$$
$$N_S = N_P - N_{SR} \quad (21)$$
3. Multi-objective functions for each stream are computed as:
$$C_I = \mathrm{Cost_I} = F(X_1^I, X_2^I, \dots . X_3^I) \quad (22)$$
4. Flow intensity in WCOA regulates solution movement—higher intensity accelerates convergence but risks overshooting, while lower intensity ensures exploration but slows progress. Flow intensity for rivers and the sea is determined by:
$$Ns_n = \mathrm{round}\left\{\left|\frac{\mathrm{Cost_n}}{\sum_{I=1}^{N_{SR}} \mathrm{Cost_I}}\right| \times N_{SR}\right\}, n = 1, 2, \dots, N_{SR} \quad (23)$$
5. Stream flow into rivers is updated as:
$$\overrightarrow{X_S^{I+1}} = \overrightarrow{X_S^{I+1}} + \mathrm{rand} \times c \times \left\{\overrightarrow{X_R^I} - \overrightarrow{X_S^{I+1}}\right\} \quad (24)$$
6. River flow into the sea is computed as:
$$\overrightarrow{X_S^{I+1}} = \overrightarrow{X_S^{I+1}} + \mathrm{rand} \times c \times \left\{\overrightarrow{X_{SEA}^I} - \overrightarrow{X_S^{I+1}}\right\} \quad (25)$$
7. The best solution updates river and stream positions, with the top solution replacing the river with the sea.
8. Evaporation removes ineffective solutions, while precipitation introduces diversity, ensuring a balance between exploration and exploitation.

These steps are essential for escaping local optima and facilitating an extensive exploration of the solution space. Evaporation discards less promising solutions, enabling focus on more viable areas, while precipitation introduces new solutions that may approach the global optimum. This cyclical process ensures a dynamic balance between exploration and exploitation, enhancing the algorithm's efficacy in finding optimal solutions.

After evaporation, the precipitation process is evaluated as:

$$\overrightarrow{X_S^{NEW}} = \overrightarrow{LB} + \text{rand} \times \left(\overrightarrow{UB} - \overrightarrow{LB}\right) \tag{26}$$

9. The maximum distance is reduced by:

$$D_{max}^{I+1} = D_{max}^{I} - \frac{D_{max}^{I}}{\text{Iteration}_{max}} \tag{27}$$

10. The algorithm terminates if the criteria are met, or repeats from step 5 otherwise.

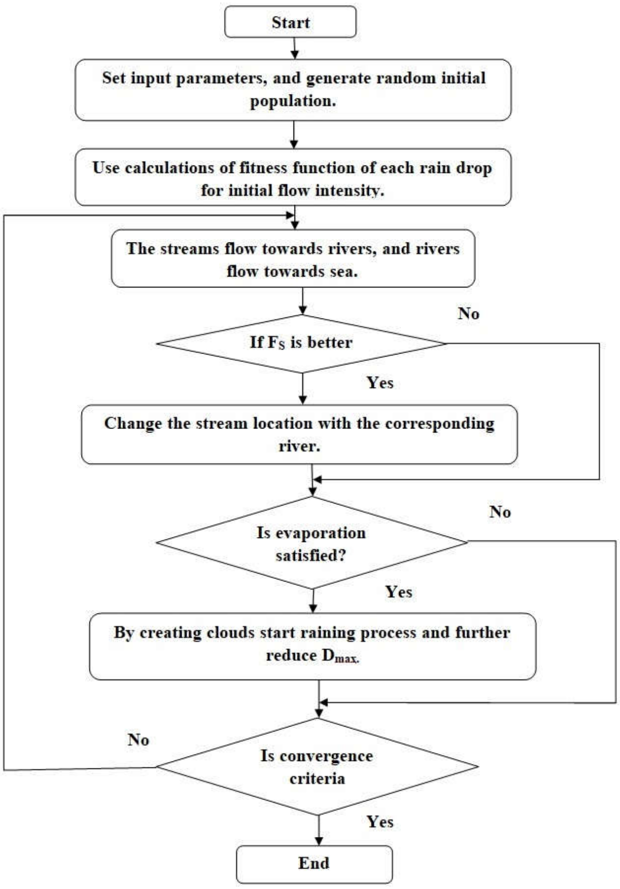

Figure 7: Flowchart for WCOA operation

5. Results and Discussion

The primary aim of the results investigation in this learning is to evaluate the organized feasibility and cost-usefulness of the WCOA method in optimizing the CHP scheme. This examination seeks to determine in case the tactic effectively balances electricity supply and demand across dispatch periods, while maintaining operations within acceptable limits. Additionally, the study assesses the potential of the WCOA method in dipping the operational expenses of the CHP system. Different functional scenarios are considered, including both CHP arrangement performance and uncertainty analysis perspectives, to evaluate the approach's cost-effectiveness under differing conditions. The analysis aims to offer perception into the realism and advantages of utilizing the WCOA method to optimize CHP operations, accounting for uncertainties and cost factors. The overall objective is to validate the strategy's effectiveness in improving operational efficiency and minimizing system costs.

This research evaluates two distinct test cases to assess the impact of uncertainty. The first case addresses the economic dispatch problem without factoring in uncertainties in wind power generation and electrical load requirement. In contrast, the second case incorporates these uncertainties, specifically the variability in wind power and load demand, into the economic dispatch representation. By comparing the two cases, the study seeks to elucidate the influence of uncertainty on system performance and optimization outcomes.

5.1 First Case: In this scenario, both power-only unit and cogeneration units are involved in the dispatch process, with cost coefficients derived from Tables 1 and 2. In this case the wind power generation and the demand load are kept fixed. The generating costs are calculated, and the best, worst, and average values of these costs are assessed. These values are then compared with the corresponding best, worst, and average costs obtained using the PSO algorithm. Table 5 presents the cost evaluations conducted through the WCOA, while Table 6 offers a comparative analysis between the proposed WCOA and the PSO algorithm.

Table 5: Costs analysis of WCOA algorithm for first case

Excellent Cost ($)	Mean Cost ($)	Awful Cost ($)
1.955786×10^5	1.997235×10^5	2.285137×10^5

Table 6: **C**omparative cost performance of WCOA and PSO algorithms for first case

Comparison Parameters	Algorithm Name	
	PSO Cost ($) [21]	WCOA Cost ($)
Cost	2.419924×10^5	1.955786×10^5

The convergence curve for this specific case is illustrated in Fig. 8.

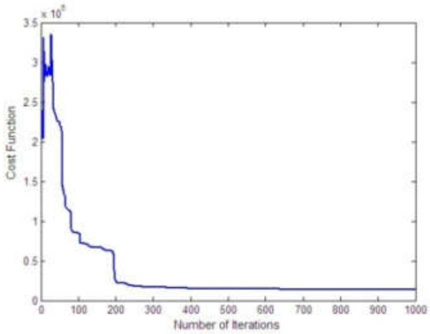

Figure 8: Convergence curve of WCOA for First case

It is noted to facilitate the cost evaluated by the WCOA algorithm is less in comparison to the cost evaluated by PSO algorithm. The WCOA hnique has given a significant savings of 23.73 %. The Fig. 9, gives an overall cost comparison of different costs evaluated for case I.

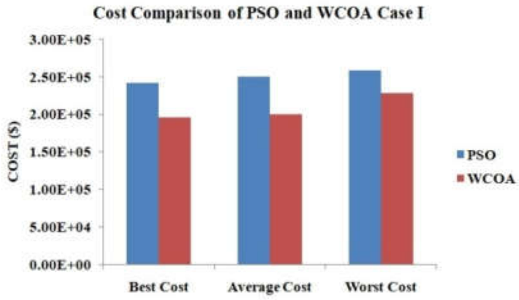

Figure 9: Cost comparisons for First case

5.2 Second Case: In this case the uncertainty of wind power and load is considered. In this scenario, wind power and load uncertainties are accounted for. The PBDED problem generates 1000 scenarios, which are reduced to 10 using the fast-forward algorithm. Table 7 displays the most excellent, mean, and most awful-case results for these scenarios. The WCOA approach yields a best cost of \$3.125886 × 10^5, as shown in Table 8, outperforming the PSO results and demonstrating superior optimization.

Table 7: Results for probabilistic analysis with WCOA algorithm for second case

Excellent Cost ($)	Mean Cost ($)	Awful Cost ($)
3.125886 ×10^5	4.418113×10^5	3.1804118×10^5

Table 8: Comparative performance of WCOA and PSO algorithms for second case

Comparison Parameters	Algorithm Name	
	PSO Cost ($) [21]	WCOA Cost ($)
Cost	3.859192×10^5	3.125886 ×10^5

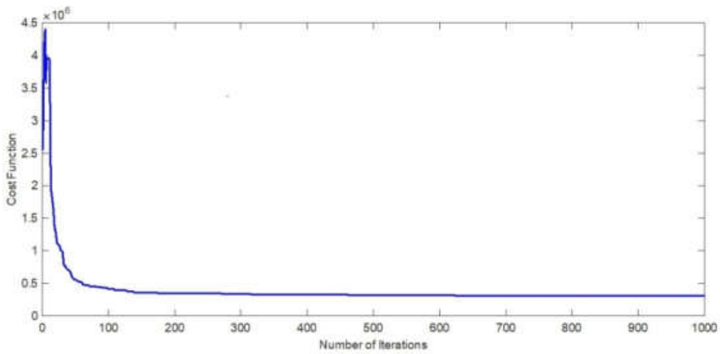

Figure 10: Convergence curve for WCOA for Second case

The convergence curve for the optimized cost obtained through WCOA algorithm is revealed in Fig. 10. Furthermore, Fig. 11 illustrates the different aspects of cost assessment among the results acquired through WCOA and PSO.

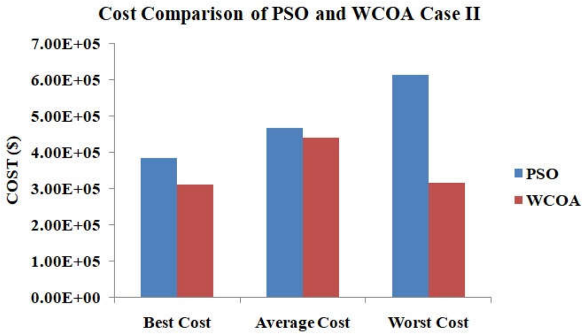

Figure 11: Cost comparisons for PBDED.

Through a comprehensive analysis, the study evaluates the virtues and precincts of the WCOA technique in managing unpredictability and minimizing the economic dispatch concern. On reviewing its performance with former methods, it assesses the WCOA algorithm's competitiveness and effectiveness in addressing challenges from anticipating errors and unpredictability's in wind power and load requirement.

6. Conclusions

This study introduces a randomized scaffold for addressing the economic dispatch issue in CHP arrangement, incorporating uncertainties in wind power and load demand. The WCOA method is applied within this framework to optimize the system's dispatch, accounting for uncertainties and multiple scenarios, providing a more accurate and reliable solution.

Unlike traditional methods, WCOA dynamically generates and evolves candidate solutions by mimicking the movement of water from higher to lower elevations. This algorithm exhibits adaptability across various problem domains, efficiently balancing exploration and exploitation through mechanisms resembling rainfall, evaporation, and runoff. By integrating probabilistic decision-making processes, WCOA effectively converges towards promising solutions while maintaining diversity among solutions to prevent premature convergence. Additionally, its parallel nature enables scalability, making it suitable for solving large-scale optimization problems. Overall, the novelty of WCOA lies in its unique conceptualization based on nature's principles, coupled with its efficiency, adaptability, and effectiveness in addressing diverse optimization challenges.

The WCOA algorithm is used in the MATLAB environment to develop and test the CHP based microgrid system in order to confirm the efficacy of the suggested method. Through simulation-based evaluation, the approach's viability and performance are evaluated in a controlled

environment. In both the cases the operational cost of the system is significantly reduced, resulting in an overall saving of 23.73% and 23.46 %.
In Case II, incorporating various scenarios with uncertainties in wind power generation and load demand in the stochastic economic dispatch results in higher costs compared to Case I, which assumes fixed values for wind power generation and load demand based on a single scenario. Consequently, the outcomes of the stochastic approach provide a more realistic and reliable representation of the problem than the deterministic approach.

The study's results reveal to facilitate the WCOA technique, offers superior optimization, vigour, and rapid convergence, making it highly suitable for economic optimization scheduling in power systems and establishing a strong foundation for future research.

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