

Starfish Optimization Algorithm for Economic Emission Dispatch with Chance Constraints and Wind Power Integration

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ABSTRACT

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This paper demonstrates the application of the Starfish Optimization Algorithm (SFOA) to solve the Economic Emission Dispatch (EED) problem considering chance constraints, integrating wind energy sources. Wind power is modeled as a Weibull distribution, and the problem is set up in the framework of Chance-Constrained Programming (CCP) to capture the variability of wind energy. The applied chance constraints ensure that the power flow equation is satisfied with a specified probability, and the resulting CCP formulation is transformed into a deterministic optimization problem using the premises of probability theory. Inspired by the peculiar behaviours of starfish, such as exploration, preying, and regeneration, the SFOA inspires strong global search capability and convergence efficiency. This approach effectively minimizes both generation costs and emissions while addressing the uncertainty associated with wind power. The method is tested on a ten-unit power system with wind energy integration, showing the robustness and efficiency of SFOA in achieving optimal solutions for the chance-constrained EED problem.

Keywords: Starfish Optimization Algorithm (SFOA), Economic Emission Dispatch (EED), Chance-Constrained Programming (CCP), Wind Power, Weibull Distribution.

INTRODUCTION

1.1 Background of Research: However, industrial growth in the past also increased energy consumption, and more conventional power generation is expensive, time-consuming. Renewable energy - especially wind - is now greatly used despite this intermittency factor to combat climatic change. The prediction of wind power output is done by using physical methods such as hybrid techniques, chaos theory, and evolutionary algorithms and statistical methods [1-2]. In thermal unit scheduling, the probabilistic nature of wind power is very crucial. Emission dispatch minimizes costs and emissions [3-5], focusing on enhancing ELD problem-solving under practical constraints, including dynamic/static cases with complex cost functions. Wind power uncertainty creates stochastic optimization problems, leading to the search for optimal solutions [6-7].

1.2 Related Works: References [8, 9] are on sampling techniques for OPF formulation based on stochastic wind farm output, with uncertainty mainly related to cost functions. Methods for solving CCPs such as sampling and integer programming [10-12] are generally conservative, whereas analytical methods use probability distributions, and Weibull is the most common one used for WES output modeling [13], where meteorological or statistical data can be used for parameter estimation [14].

These studies [15-17] incorporate wind and solar energy in the optimal power flow models that examine economic emission dispatch, carbon trading fluctuations, and renewable-integrated systems. Major contributions include the works on emission optimization with wind power [20], multi-objective economic dispatch using NSPSO [21], and power flow optimization with stochastic wind power [22]. Economic and emission dispatch optimization for renewable systems has been developed by using HSA [23] and improved flower pollination algorithms [24].

Efficient CSCA [25] and improved NSGA [26] balance cost and emissions in wind-integrated systems. Fuzziness-based EED methods are good for the optimization of trade-off but weak for nonlinear models. Hybrid GA-PSO approaches improve convergence but increase the computational complexity, which is reduced by the SFOA optimization strategy [27].

1.3 Main contributions: The main contributions of this study are

- SFOA Proposal: The Starfish Optimization Algorithm (SFOA) addresses the Economic Emission Dispatch (EED) problem with Wind Energy Sources (WESs), incorporating a chance constraint for wind power uncertainty.
- Two-Phase Structure: SFOA combines hybrid search strategies for exploration and starfish-inspired behaviours for exploitation.
- Comparative Analysis: SFOA outperforms other optimization algorithms in solving the chance-constrained EED problem.

1.4 Structure of the paper: The structure of the paper is as follows: Section 2 outlines the formulation of the CCED problem. Section 3 describes the SFOA. Section 4 provides experimental results, comparing the proposed method for the CCEED problem, including thermal units and Wind Energy Sources (WES). Section 5 concludes with the key findings and suggestions for future research.

Problem Formulation of Economic Dispatch with Chance Constraints

This develops a chance-constrained EED model in order to incorporate wind power uncertainty so as to minimize total production cost and emissions -CO, CO₂, NO_x. The VPLE would be accounted for within the model by making use of a sinusoidal term added into the cost function. The decision variables are the thermal unit power outputs P_i , with total cost and emission functions defined by equations (1) and (2).

$$\text{Cost}_T = \sum_{i=1}^N a_i + b_i P_i + c_i P_i^2 + \left| d_i \sin \{e_i (P_i^{\min} - P_i)\} \right| \quad (1)$$

$$\text{Emission}_T = \sum_{i=1}^N \alpha_i + \beta_i P_i + \gamma_i P_i^2 + \eta_i \exp(\lambda_i P_i) \quad (2)$$

Problem Constraints: The CCEED problem's deterministic constraints are the thermal units' generation limits.

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad i = 1, 2, \dots, N \quad (3)$$

Introducing WES into the EED model will add a stochastic constraint. The chance constraint specifying the permissible tolerance for power imbalance among load, thermal power, WES output (W), and system losses is as in (4).

$$P_r \left\{ \sum_{i=1}^N P_i + W \leq P_D + P_L \right\} \leq \sigma \quad (4)$$

Here P_L calculated using equation (5)

$$P_L = \sum_{i=1}^N \sum_{j=1}^N P_i B_{ij} P_j + \sum_{i=1}^N B_{0i} P_i + B_{00} \quad (5)$$

The variability in Wind Power (WP) generation arises from fluctuating wind speeds, with the WP output W being a function of the wind speed V [26].

$$W = \begin{cases} 0, & \text{if } V < v_{in} \text{ or } V > v_{out} \\ \frac{(V - v_{in}) * w_r}{v_r - v_{in}}, & \text{if } v_{in} \leq V < v_r \\ w_r & \text{if } v_r \leq V < v_{out} \end{cases} \quad (6)$$

Wind turbine rated power is w_r , cut-in/out wind speeds represented by v_{in} and v_{out}

This study models wind speed randomness using a two-parameter Weibull distribution, expressed as:

$$f_v(v) = \frac{k}{c} * \left(\frac{v}{c}\right)^{k-1} * \exp\left[-\left(\frac{v}{c}\right)^k\right] \quad (7)$$

Thus, the Cumulative Distribution Function (CDF) is expressed as:

$$F_v(v) = \int_0^v f_v(\tau) d\tau = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right] \quad v \geq 0 \quad (8)$$

$k \rightarrow$ Scale Factor; $c \rightarrow$ Shape Factor; $v \rightarrow$ Wind Speed

Mathematical Model of Starfish Optimization Algorithm

In the initialization step of the Starfish Optimization Algorithm, the starfish positions are generated randomly in the design variable bounds as follows:

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1D} \\ X_{21} & X_{22} & \dots & X_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ X_{N1} & X_{N2} & \dots & X_{ND} \end{bmatrix}_{N \times D} \quad (9)$$

Here, X is the $N \times D$ matrix of the starfish positions where N is the population size and D is the number of design variables. Each starfish position is calculated using Eq. (9).

$$X_{ij} = l_j + \text{rand}(0,1) * (u_j - l_j), \quad j = 1, 2, \dots, D, \quad i = 1, 2, \dots, N \quad (10)$$

Fit values are calculated from the objective function and stored by equation (11).

$$F = [F(X_1) \ F(X_2) \ \dots \ F(X_N)]^T_{N \times 1} \quad (11)$$

For $D > 5$, starfish utilize all five arms and knowledge of the finest position to guide their exploration in the search space.

$$\begin{cases} Y_{i,p}^T = X_{i,p}^T + a_1(X_{best,p}^T - X_{i,p}^T)\cos\theta, & \text{rand} \leq 0.5 \\ Y_{i,p}^T = X_{i,p}^T - a_1(X_{best,p}^T - X_{i,p}^T)\sin\theta, & \text{rand} > 0.5 \end{cases} \quad (12)$$

θ and a_1 are calculated as follows:

$$a_1 = (2r - 1)\pi \quad (13)$$

$$\theta = \frac{\pi}{2} \cdot \frac{T}{T_{max}} \quad \begin{cases} T \rightarrow \text{Current iteration} \\ T_{max} \rightarrow \text{Maximum iteration} \end{cases} \quad (14)$$

For $D > 5$, the five-dimensional search pattern updates five position dimensions to enhance search efficiency. If the updated position exceeds the boundaries, the arms retain the previous position.

$$X_{i,p}^{T+1} = \begin{cases} Y_{i,p}^T & l_{b,p} \leq Y_{i,p}^T \leq u_{b,p} \\ X_{i,p}^T & \text{otherwise} \end{cases} \quad (15)$$

For $D \leq 5$, the exploration phase uses a unidimensional search pattern, with one arm moving based on other starfish's positions.

$$Y_{i,q}^T = E_t X_{i,p}^T + (X_{k_1,p}^T - X_{i,p}^T) * A_1 + (X_{k_2,p}^T - X_{i,p}^T) * A_2 \quad (16)$$

Here, $X_{k_1,p}^T$ and $X_{k_2,p}^T$ are p-dimensional positions, A_1 and A_2 are random numbers between $(-1,1)$, and E_t is the starfish's energy.

$$E_t = \frac{T_{\max} - T}{T_{\max}} \cos \theta \quad (17)$$

If the position exceeds boundaries, the starfish retains the previous position. In the exploitation phase of SFOA, starfish positions are adjusted through a dual-directional search considering the best position and relative distances to other starfish.

$$d_m = \left(X_{\text{best}}^T - X_{m_p}^T \right), \quad m = 1, \dots, 5 \quad (18)$$

In the predatory behaviour, the positions are updated using five distances from the global best (d_m) and five randomly selected starfish (m_p).

$$Y_i^T = X_i^T + r_1 * d_{m1} + r_2 * d_{m2} \quad (19)$$

In the preying phase, starfish move towards or away from optimal solutions based on random values and selected distances. The regeneration phase adjusts the position of the last starfish due to predator effects.

$$Y_i^T = \exp(-T \times N / T_{\max}) X_i^T \quad (20)$$

If the location calculated from Eq. (19) or Eq. (20) exceeds the design variable limits, it is adjusted to stay within the specified boundaries.

$$X_i^{T+1} = \begin{cases} Y_i^T & l_b \leq Y_i^T \leq u_b \\ l_b & Y_i^T < l_b \\ u_b & Y_i^T > u_b \end{cases} \quad (21)$$

Simulation Results

A ten-unit system is used to assess the performance of the proposed technique in solving the multi-objective EED problem. The analysis takes into account transmission losses, valve point loading effect (VPLE), and generation capacity constraints. The unit data, as provided in [25], totals a power load of 2000 MW.

Performance and accuracy of the proposed SFOA method to solve the stochastic EED problem are assessed with two test scenarios that have different levels of complexity and system losses in a ten-unit system.

Case 1: 10-unit system without WES.

Case 2: 10-unit system with WES.

Table 1: Parameters of wind turbine

K	vr	vout	C	vin
1.7	15	45	15	5

Table 2: Proposed SFOA Parameters

Parameter	Value
Itermax	200
Population size (N)	200
Global Parameter	0.5
Number of arms	5

The SFOA technique is compared with other metaheuristic techniques to evaluate its effectiveness. This chapter also examines the impact of wind parameters on optimal generation and the objective functions.

4.1. Case 1: 10-unit system without WES

This section deals with EED problem irrespective of wind power. The best-cost and best emission convergence curves under the proposed algorithm SFOA are demonstrated, respectively in Fig. 1 and Fig. 2 where the optimum convergence for algorithm has occurred around 88 iterations for the lowest cost and iteration 147 regarding the least emitted value.

The results show the performance of the optimization algorithm focused on minimizing fuel cost and emissions in a power system. The decrease in the fuel cost is very sharp in the first iterations and eventually stabilizes at the minimum cost after 50 iterations. Similarly, the decrease in the emissions shows steep reduction during the first 20 iterations and stabilizes at about 3800 tons/hr. The consistent trend of two plots reflects the efficiency of the proposed algorithm in achieving considerable improvements by the limited number of iterations. Such rapid convergence delivers low computational effort with satisfactory accuracy. The results emphasize the applicability of the algorithm for real-time application, particularly in energy-economic dispatch. The optimization process accurately balances cost and environmental perspectives and is hence suitable for sustainable power system operations.

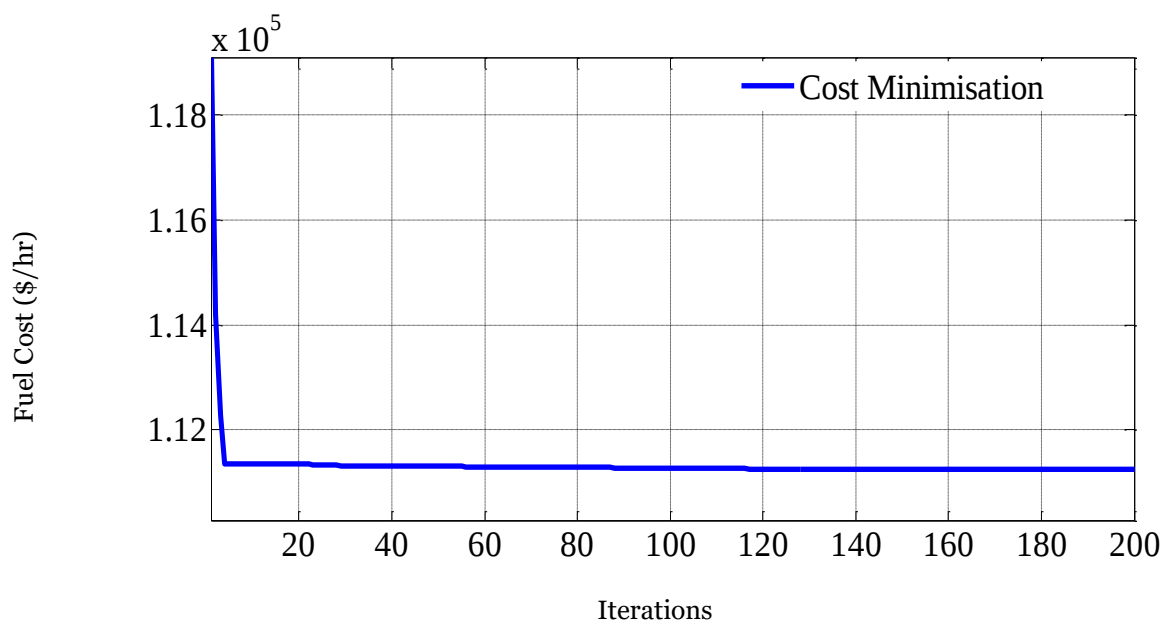


Figure 1. Convergence characteristics of Cost minimisation Case-1

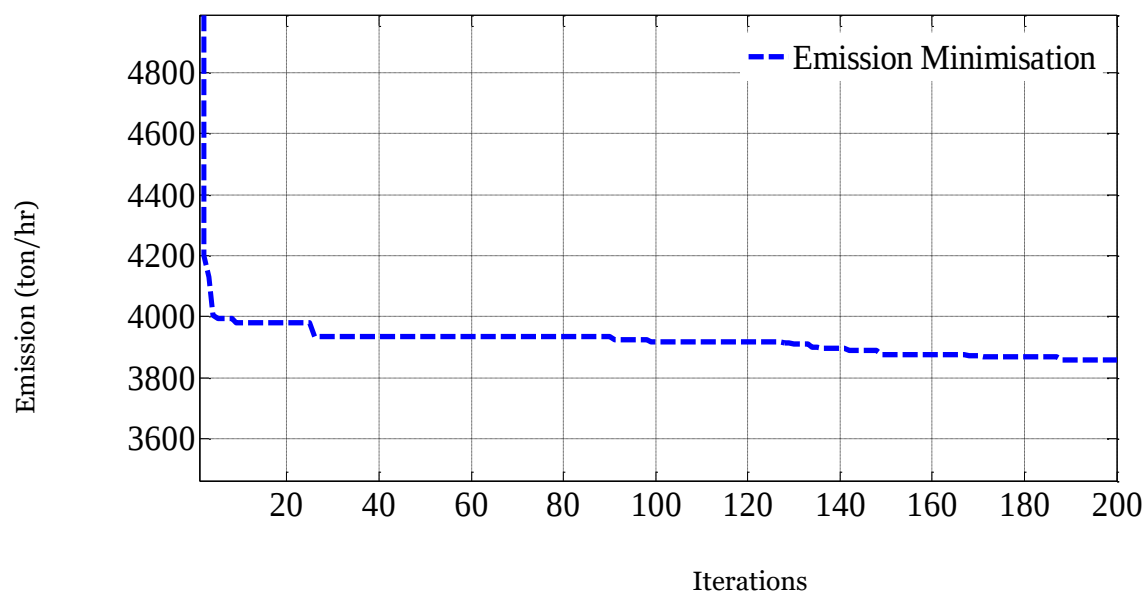


Figure 2. Convergence characteristics of Emission minimisation Case-1

Here, for the ED problem, SFOA yields lower fuel cost as against NSGA-II [26], namely, 111,260.30 \$/hr vs. 111,497.63 \$/hr. For the Emission Dispatch problem, SFOA also exhibits relatively better cost performance, 116,386.45 \$/hr versus 116,412.46 \$/hr. Emission outputs are much decreased in Emission Dispatch. SFOA achieved 3859.21 tons/hr whereas NSGA-II [26] is 3932.24 tons/hr, hence indicating the high reduction of emission as compared to the other. The power loss in Emission Dispatch is a bit lesser for both algorithms, though marginally, with SFOA.

From the Economic Dispatch results, it is clear that SFOA had the least cost of \$111260.2963 with the lowest amount of emissions to be 4443.6699 ton/h, bettering PSO [26] (\$111498.49, 4567.27 ton/h), DE [26] (\$111565.71, 4572.68 ton/h), and FA [26] (\$111500.79, 4581 ton/h). For Emission Dispatch, SFOA also performed well with the lowest emissions of 3859.212 ton/h and a cost of \$116386.4473, compared to PSO [26] (\$116412.49, 3932.24 ton/h), DE [26] (\$116418.34, 3946.24 ton/h), and FA [26] (\$116443.05, 3932.62 ton/h). This shows that SFOA is the best method in minimizing both cost and emissions.

Table 3: Optimal and Comparison results for Case-1

Unit	SFOA		NSGA-II [26]	
	Economic dispatch	Emission dispatch	Economic dispatch	Emission dispatch
P1	54.9992	55.0000	55.0000	55.0000
P2	80.0000	80.0000	80.0000	80.0000
P3	107.3467	63.3443	106.9408	81.1394
P4	99.9944	60.1998	100.5756	81.3666
P5	82.2685	160.0000	81.5017	160.0000
P6	82.4356	240.0000	83.0207	240.0000
P7	300.0000	300.0000	300.0000	294.4853
P8	340.0000	340.0000	340.0000	297.2669
P9	470.0000	409.9616	470.0000	396.7628
P10	470.0000	373.6305	470.0000	395.5738
CT (\$/hr)	111260.2963	116386.4473	111497.6300	116412.4600
ET (ton/hr)	4443.6699	3859.2120	4572.1900	3932.2400
PL (MW)	87.0445	82.1401	87.0388	81.5949

4.2. Case 2: 10-unit system with WES

In this scenario, the base ten-unit system with another wind farm that has 50 turbines, 2 MW each, is used to evaluate for a total demand of PD=2000 MW. The effects of wind power (WP) penetration on the Economic-Emission Dispatch (EED) problem are explored based on the various threshold tolerances (σ). Fig. 3 illustrates the Pareto front generated using the SFOA, wherein a reduction in σ increases costs and emissions since WP utilization decreases. Conversely, higher σ enhances WP penetration and reduces both the production cost and emissions as summarized in Table 9.

The results show that maximum cost and emissions occur without WP, and higher σ yields significant reductions. However, practical constraints limit σ to smaller values to mitigate risks of insufficient WP. It is also interesting to note that the wind farm contributes only when $\sigma \geq 0.14$, meaning that appropriate tolerance levels are very important for reliable system operation.

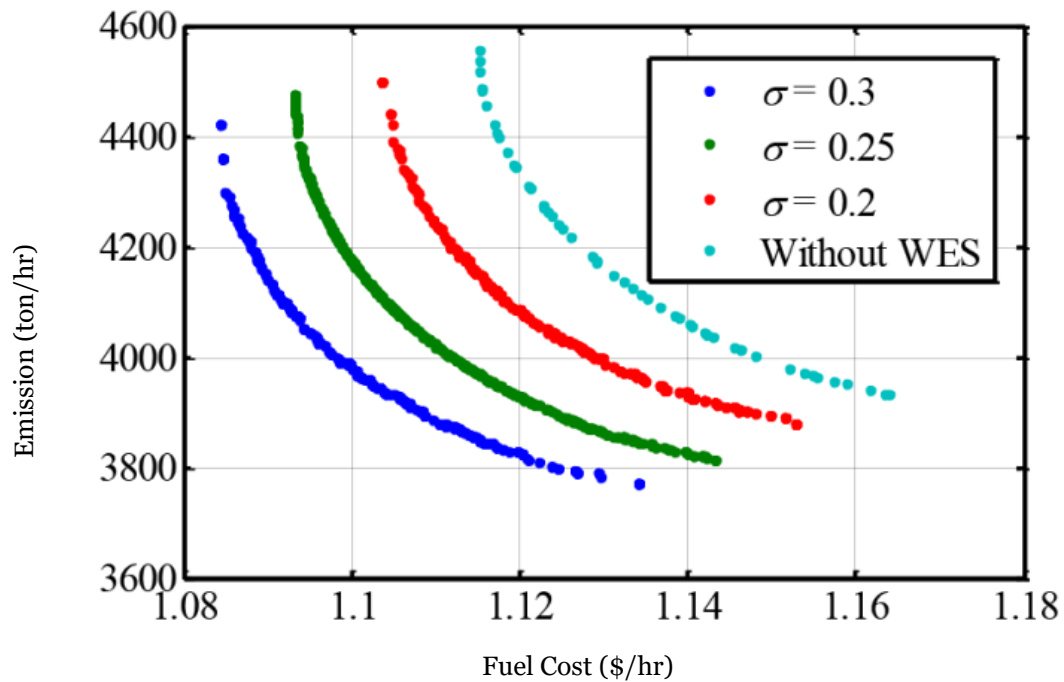


Figure 3. Impact of Threshold Tolerance on Pareto Solutions

The figure 4 show the effect of integration of WES into a power system on fuel cost and emissions analyzed over 200 iterations in three scenarios: no WES, WES (tolerance = 0.2), and WES (tolerance = 0.3). From figure 3, the fuel cost graph, the lowest cost occurs without WES, as the conventional generators are fully utilized. With WES at lower tolerance ($\sigma=0.2$), fuel costs are slightly higher due to less wind power integration. At higher tolerance ($\sigma=0.3$), fuel costs are highest because of the increased reliance on wind power, which introduces variability and requires compensatory adjustments from conventional units.

The figure 5 shows that emissions are highest without WES since the system is fully dependent on conventional generation. In addition, the integration of WES reduces emissions, and higher tolerance ($\sigma=0.3$) results in the lowest emissions due to increased penetration of wind power. The results show that there is a trade-off between fuel cost and emissions: increasing wind power penetration reduces emissions but increases costs. All scenarios converge within the first 50 iterations, which prove the efficiency of the optimization process and the importance of balancing economic and environmental goals in power system operations.

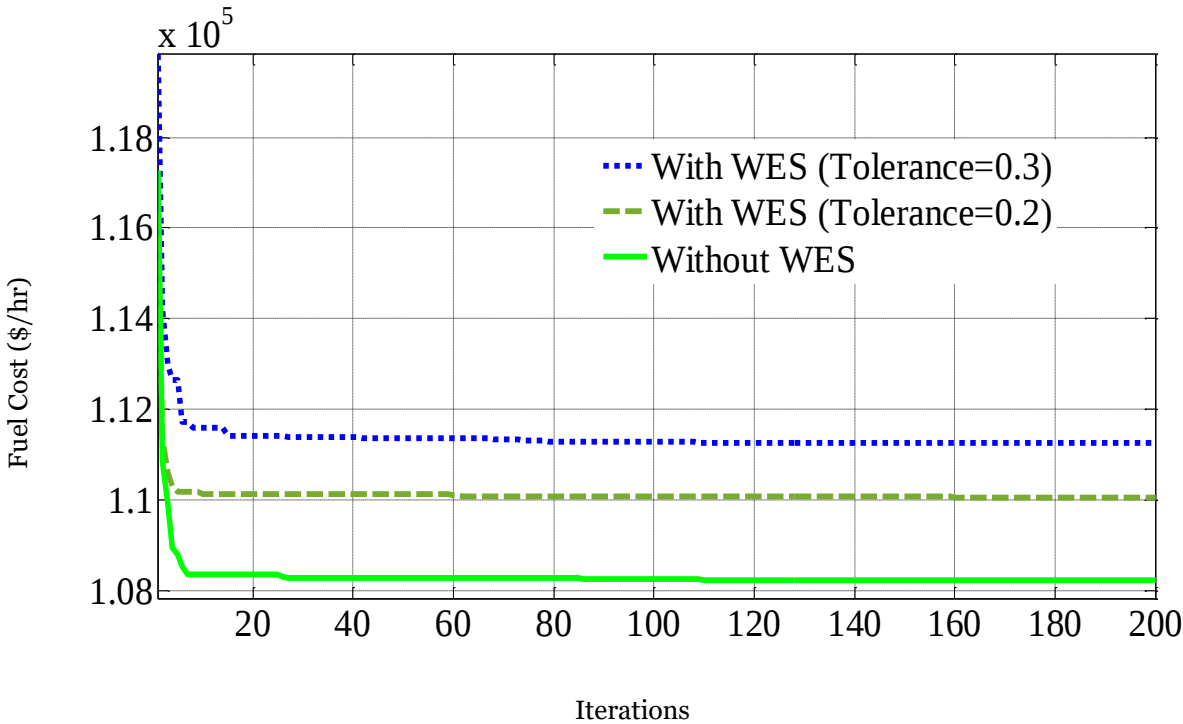


Figure 4. Convergence characteristics of Cost minimisation Case-2

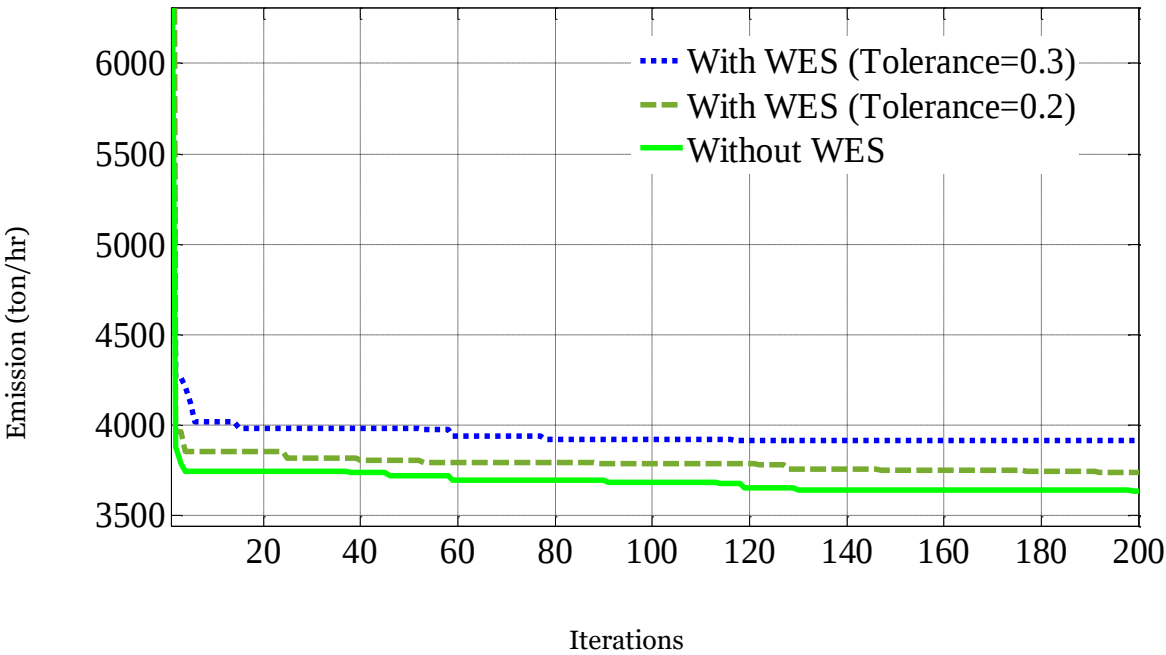


Figure 5. Convergence characteristics of Emission minimisation Case-2

Table 4: Optimal results for Case-2 SFOA

	Economic dispatch		Emission Dispatch	
$\sigma(\text{Tolerance})$	0.2	0.3	0.2	0.3
P1	55.0000	55.0000	55.0000	55.0000
P2	80.0000	80.0000	80.0000	80.0000
P3	99.4419	98.0780	79.1093	74.1897

P4	89.5834	85.1351	78.1815	81.0133
P5	89.9765	69.2188	160.0000	160.0000
P6	79.9445	70.6700	240.0000	240.0000
P7	300.0000	300.0000	300.0000	300.0000
P8	340.0000	340.0000	340.0000	340.0000
P9	470.0000	470.0000	364.6705	373.0324
P10	470.0000	470.0000	364.4611	325.5479
WP	17.0373	45.6885	17.1171	47.5989
CT, \$/hr	110160.0199	108266.3721	115342.5480	113685.0657
ET, tonnes/hr	4433.9483	4323.1712	3847.4873	3684.5482
PL(MW)	85.8598	84.0536	79.3843	76.5148

The integration of wind energy systems under ED and EmD scenarios proves to be one of the essential advantages with increased tolerance levels at $\sigma=0.3$. In both ED and EmD, the high WP contribution diminishes the contribution of conventional units, especially the units P5 to P10, thus augmenting the total penetration of renewable energy. WP contribution increases up to 45.69 MW in ED and 47.60 MW in EmD under $\sigma=0.3$. Thus, the overall cost and emission decrease, where ED decreases from \$110,160.02/h ($\sigma=0.2$) to \$108,266.37/h ($\sigma=0.3$), and emission decreases from 4433.95 tons/h to 4323.17 tons/h. EmD decreases in a similar pattern, implying that the use of higher WP is beneficial from both economic and environmental perspectives.

Moreover, the power losses (PL) also decrease with increasing WP integration; ED reduces from 85.86 MW to 84.05 MW, and EmD reduces from 79.38 MW to 76.51 MW. Here, EmD focuses on emissions reduction, which implies lower emissions at $\sigma=0.3$; for example, 3684.55 tons/h as against ED. It is, however, at a cost of overall expenses being a little higher. The results show the efficiency of higher tolerance levels in optimizing WES integration, with a balance between economic objectives, such as lower costs, and environmental goals, such as reduced emissions, and also with reduced power losses.

CONCLUSION

RESs, such as wind turbine systems, are increasingly included in power grids to reduce dependence on fossil fuels and mitigate the detrimental effects of conventional generation technologies on the environment. However, the nature of RESs, especially wind power due to weather fluctuations, presents difficulties for stable grid operation. To address the aforementioned problem, this study suggests a meta-heuristic-based solution to the combined EED problem integrated with wind turbine power generation. This solution includes the randomness in wind power generation through the Weibull distribution function and then transforms the traditional deterministic power balance constraint into a chance constraint. In addition to these constraints, the problem statement also accounts for additional operating constraints such as generation limits, ramp rate limits, and POZ. Because the problem is complex, nonlinear, and nonconvex, this research study will employ an elitist optimization method known as Stochastic Fish Optimization Algorithm (SFOA) in the finding of optimal solutions. The suggested strategy will be tested on a ten-unit power system with its results compared with other optimization techniques. It highlights the success of the method and suggests this method can be extended to cover hybrid EED problems, for example, integration of wind farms and photovoltaic (PV) systems.

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