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MODIFIED PARTICLE SWARM OPTIMIZATION: A SOLUTION OF ECONOMIC LOAD DISPATCH PROBLEM FOR AN ISLANDED MICROGRID

Asif A. Rahimoon[a], Mohd Noor Abdullah[a*], Halyani Mohd Yassim [a,b], Jasrul Jamani Jamian[c,d], Sabir Ali Kalhoro[e], Asif Raza[f]

[a]Green and Sustainable Energy (GSEnergy) Focus Group, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Parit Raja, Batu Pahat, Johor, Malaysia.
[b]Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka (UTeM), Hang Tuah Jaya, 76100 Durian Tunggal, Malaysia.
[c]Research and Development (R&D) Director, Sustainable & Innovation Engineering Sdn Bhd, Malaysia.
[d]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia
[e]University of North Dakota state University, United States.
[f]School of information science and engineering, NingboTech University of Ningbo, China.

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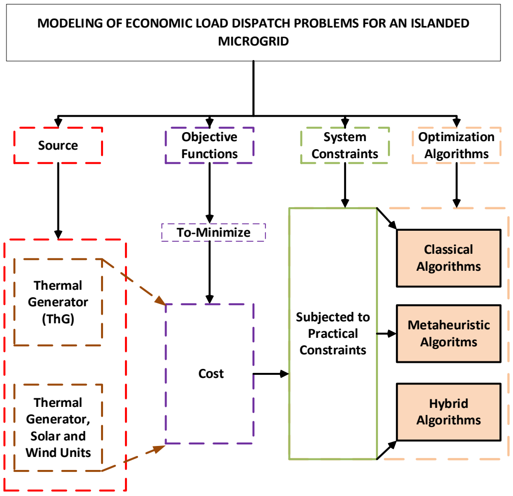
*Corresponding author
mnoor@uthm.edu.my

Graphical abstract



Abstract

Economic load dispatch (ELD) in power generation has evolved from prioritizing cost optimization using conventional fossil-fuel generators to emphasizing the incorporation of renewable energy (RE) sources. Several studies have been conducted to non-convex ELD problems by using particle swarm optimization (PSO). However, this solution suffers to trap at local minima especially for multimodal problems. Therefore, in this study modified particle swarm optimization (M-PSO) algorithm incorporating velocity and position clamping strategy is proposed to address the challenges in islanded microgrid (MG) considering thermal, solar and wind units. This strategy regulates the particle movement to prevent divergence and enforce boundary constraints, ensuring feasible and stable convergence. This enhances solution quality by maintaining a controlled exploration-exploitation trade-off within the defined search space. The proposed M-PSO has been tested under two different ELD problem scenarios; 1) ELD with thermal generators, 2) ELD with thermal generators, solar and wind units. The proposed M-PSO can minimize the total cost about 5.2457% in the scenario-2 as compared scenario-1. The proposed M-PSO algorithm provided significant cost savings of 0.6334% in scenario-1 and 9.0427% in scenario-2 when compared to the reduced gradient method (RGM) algorithm.

Keywords: Economic load dispatch, renewable energy sources, islanded microgrid, Modified particle swarm optimization (M-PSO), optimal solutions**.**

1.0 INTRODUCTION

The microgrid (MG) is a localized energy system consisting of conventional sources or renewable energy sources (RESs), energy storage facility, and loads [1]. Generally, MG have two modes of operation as; independent mode referred as an islanded mode, balances the power demand (PD) independently, while the grid-connected mode, and enable MG to interact with the main grid [2]. The ELD problem remains a critical concern in both operating modes of a MG, aiming to allocate generated power from available sources to meet the required PD incorporating minimum fuel costs functions and system constraints [3]. The utilization of single source specifically conventional type from MG to evaluate ELD problem can lead to high cost for dispatching the generated power. Thus the current research has recently shifted on integration of RESs to reduce the total generation cost under single and multi-objective optimization problems [4]. The ELD problem can be modelled in simple, complex and non-convex functions considering the coefficients as, valve point effects (VPE), generation capacity limit (GL), power losses (PL), prohibited operating zone (PoZ) and ramp rate limit (RRL) constraints [5].

However, the ELD problem associated to an islanded MG is a single objective optimization problem and demands an optimal solution on choice from classical, meta-heuristic and hybrid types. Depending on the variations in power demand (PD), the ELD problem can be classified into static and dynamic cases [6]. Classical solutions such as quadratic programming (QP), lambda iteration (LI), gradient methods, lagrangian relaxation (LR), dynamic programming and linear programming can be used for ELD problems.

Nevertheless, these solutions are fixed structured based and need less expertise; often stuck in finding local optima while solving complex and large scaled ELD problems [7]. To achieve this shortcoming, meta-heuristic and hybrid solutions have gained popularity for minimizing the cost values for islanded MG [8]. In recent years, a variety of meta-heuristic methods have been proposed to address the complex and non-convex nature of the ELD problems.

This include evolutionary algorithms (EA), harmony search algorithm, differential evolution based algorithms, teaching and learning based optimization algorithms, grasshopper optimization algorithm, grey wolf optimizer algorithm, Ant lion optimizer algorithm, artificial bee colony algorithm, moth-flame optimizer algorithm, lightning search algorithm, tabu search algorithm, simulated annealing algorithm, shuffled frog leaping algorithm, genetic algorithm and PSO [9].

Among these, GA and PSO are widely recognized as the most prominent and frequently applied meta-heuristic methods, particularly in overcoming the limitations of traditional deterministic approaches, either in their standard forms or through hybridization [10]. However, both methods often face challenges such as high computational time and the need for careful parameter tuning, especially when dealing with large-scale or highly complex problems.

In context to use of new and advanced solutions for ELD problem the recent studies like as squirrel search algorithm (SSA), was tested under; 6, 10, 13, 40, 110, 140 and 160, ThG units to investigate the exploration and exploitation characteristics with PB, GL and VPE coefficients [11]. The optimal cost achieved from this study were reported as; $15442.4/h, $623.71/h, $17963.82/h, $121412.34/h, $1559818.72/h and $9993.62/h respectively.

The hybrid harris hawks optimizer (HHO), was tested for different case studies including 3, 6, 13, 15, 40 and 140 ThG units with PB, GL, VPE, RRL, PL and PoZ coefficients [12]. The final costs obtained from HHO algorithm were $15444.19/h, $17960.43/h, $32,694.73/h, $121414.83/h and $1,559,748.49/h respectively

The hill-climbed sine–cosine (HcSC), algorithm was tested on 15, 40, 80, 110 and 140 ThG units including PB, GL, VPE, RRL, PL and PoZ coefficients and the resulted costs for ELD problem were $32691.64/h, $10500/h, $21515.82/h, $197988.16/h and $1559708.47/h [13] respectively.

The equilibrium optimizer (EO) algorithm, had been tested on 13, 15 and 140 ThG units based on PB, GL, VPE, RRL, PL and PoZ coefficients [14]. The obtained minimum cost saving values from EO algorithm are $17973.41/h, $32,701.18/h and $1653800/h.

An adaptive hook-jeeves algorithm (HJA), had been simulated with consideration of 3, 6 and 13 ThG units on basis of as PB, GL, VPE, RRL, PL and PoZ coefficients. The optimal result obtained from this study in shape of cost saving were $8234.07/h, $15442.80/h and $17960.36/h [15].

A recent study on marine predator algorithm (MPA) has been evaluated in improved and modified forms as nonlinear (NMPA) to solve ELD problems incorporating PB, GL, VPE, RRL and PoZ constraints [16]. The final cost values achieved using improved MPA are much lower than the results obtained from the standard MPA and NMPA.

Although numerous studies have addressed the ELD problem in the literature, there remains a critical need to identify more effective solutions that offer robust exploration and exploitation capabilities. In this context, the key contributions of the present study are outlined as follows:

- A modified particle swarm optimization (M-PSO) incorporating , an improvement factor, velocity and position clamping strategy and velocity mirror effects is proposed to maintain the stability and convergence of the search process by preventing particles from diverging the optimal region.
- The supremacy of proposed M-PSO under two different scenarios of ELD problem for islanded MG system involving thermal, solar and wind units have been demonstrated.
- The proposed M-PSO gained lowest total generation cost in contrast to existing solutions to justify the algorithm authenticity.

2.0 ECONOMIC LOAD DISPATCH (ELD) PROBLEM FORMULATION

This section presents the formulation of the ELD problem, which incorporates thermal, solar, and wind generation units with the objective of minimizing the total fuel cost of power generation. There is no trade of energy as the selected microgrid is in islanded mode of operation. The objective functions of generation units are described as follows.

2.1 Thermal Generation Cost Function

The cost function $F_{cost}(P_{Gi})$ for thermal generator (ThG) in ($/h) generally represented through the quadratic function as given in Eq. (1) [17].

$$F_{cost}(P_{Gi}) = \sum_{i=1}^{N_g}(u_i P_{Gi}^2 + v_i P_{Gi} + w_i) \tag{1}$$

where, P_{Gi} corresponds to the total power generation of thermal unit in MW and u, v and w are the fuel coefficients of the i^{th} generator [17].

2.2 Solar Generation Cost Function

The cost function for solar unit in $/h can be written as in Eq. (2) [17].

$$F_{Cost}(solar) = aI^{S}P_{Solar} + G^{s}P_{Solar} \tag{2}$$

$$a = \frac{r}{(1-(1+r)^{-N})} \tag{3}$$

where, a represents the annuitization coefficient which is based on interest scale (r) with value of 0.09 is shown in Eq. (3). While, other linked parameters such as investment duration (N) valued of 20 years, I^S denote the ratio between the investment cost and the power output per unit numerically taken as $5/MWh. Moreover, G^S represent the operational and maintenance (O&M) cost of solar unit and taken as $0.000016/MWh and P_{Solar} denote the solar generation in MW [17]. Hence, the $F_{Cost}(solar)$ can be re-defined and calculated using the Eq. (4) as follows [17]:

$$F_{Cost}\ (solar) = 0.5477483 * P_{Solar} \tag{4}$$

2.3 Wind Generation Cost Function

The cost function unit in $/h of wind generation can be written as in Eq. (5) [17].

$$F_{Cost}(wind) = aI^W P_{Wind} + G^W P_{Wind} \tag{5}$$

where, a represents the annuitization coefficient which is based on interest scale (r) same as shown in Eq. (3). However, I^W presents the ratio of investment cost of wind unit to unit power taken as $1.4/MWh, G^W reflects the O&M cost considered as $0.000016/MWh and P_{Wind} denote the wind generation in MW. Therefore, the equation (5) can be re-written as Eq. (6) [17].

$$F_{Cost}(wind) = 0.1533810 * P_{Wind} \tag{6}$$

2.4 ELD Problem Function

The ELD problem function is mathematically drafted involving $F_{cost}(P_{Gi})$ $F_{Cost}\ (solar)$ and $F_{Cost}(wind)$ functions respectively as shown in Eq. (7).

$$Min\ F_{CTotal} = \sum_{i=1}^{N_g}\left(u_i P_{Gi}^2 + v_i P_{Gi} + w_i\right) + 0.5477483 * P_{Solar} + 0.1533810 * P_{Wind} \tag{7}$$

2.5 Constraints

The power balance (PB) and generation limit (GL) constraints are considered to formulate the ELD problem for minimizing the total generation cost [17].

2.5.1 Power Balance Constraint

This constraint is important to determine that the total generation from all utilized sources must be equal to power demand as shown in Eq. (8).

$$P_D = \sum_{i=1}^{N_g} P_{Gi} + P_{Solar} + P_{Wind} \tag{8}$$

2.5.2 Generation Limit Constraint

This constraint ensures that the output power of each generating unit remains within specified minimum and maximum limits as shown in Eqs. (9) to (11).

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{9}$$

$$0 \leq P_{Solar} \leq P_{Solar}^{max} \tag{10}$$

$$0 \leq P_{Wind} \leq P_{Wind}^{max} \tag{11}$$

where, P_{Gi}^{min} represents the minimum generation output and P_{Gi}^{max} present the maximum generation output of thermal generators, P_{Solar}^{max} and P_{Wind}^{max} present the maximum generation output of solar and wind units.

2.5.3 Fitness Function Formulation

The fitness function not only minimizes the total generation cost but also ensures that the power balance and generation limit constraints are satisfied. The fitness function $(F_{\_Fitness})$ is expressed as Eq (12).

$$F_{\_Fitness} = Min\ F_{CTotal} * (1 + q * V_{PB}) \tag{12}$$

where $Min\ F_{CTotal}$ is the total minimum generation cost defined in Eq. (7), q is a violation penalty factor, and V_{PB} represents the power balance violation index defined as in Eq (13) below.

$$V_{PB} = \max\left(1 - \frac{\sum_{i=1}^{N_g} P_{Gi}}{P_D - (P_{Solar} + P_{Wind})}\right), 0 \tag{13}$$

If the PB constraint of Eq. (8) is satisfied, V_{PB} = 0; otherwise, infeasible solutions are penalized proportionally. This penalty mechanism ensures that particles violating the constraint are guided back toward feasible regions of the search space.

3.0 PROCEDURE OF MODIFIED PARTICLE SWARM OPTIMIZATION (M-PSO) ALGORITHM FOR ELD PROBLEM

This section describes the proposed modified particle swarm optimization (M-PSO) algorithm developed to solve the ELD problem. Additionally, an improvement factor, velocity and position clamping strategy and velocity mirror effects are introduced to manage generation capacity constraints and to control the exploitation behavior inherent in the traditional PSO algorithm. The flowchart illustrating the M-PSO process is presented in Figure 1. The detailed implementation of the proposed MPSO is described as follows:

Step1: Initialization of M-PSO Parameters.

Set up the necessary parameters for the M-PSO algorithm, including: population size of swarm (Npop), number of iteration, C_1, C_2, inertia weight, number of runs, generation capacity limit as presented in Eqs. (9) to (11) respectively and satisfy the power balance constraints as shown in Eq. (8).

Step 2: Start Evaluation Function.

The fitness of each particle is assessed based on the ELD problem function, represented in Eq. (12). This function aims to reduce the total generation cost in term of F_{CTotal} ($/day), while that the power balance violation criteria are met.

Step 3: Initialization of particle best position (P_{best}) and global best position (G_{best})

In Step 2, the initial particles are assigned as the initial P_{best} values, and the best fitness value among them is designated as G_{best}.

Step 4: Update the particle position and velocity.

Each particle's position is updated by adding velocity (B^i) to the current position (A^i) , as expressed by Eq. (14). The velocities of i^{th} dimension are updated within the range of $[-B^i_{min}, B^i_{max}]$ by using the Eq. (15).

$$A^i(t+1) = A^i(t) + B^i(t+1) \tag{14}$$

$$B^i(t+1) = w(t) * B^i(t) + C_1(\mathrm{t}) * r_1\left[P^i_{best}(t) - A^i(t)\right] + C_2(\mathrm{t}) * r_2\left[G^i_{best}(t) - A^i(t)\right] \tag{15}$$

$$w(t) = w_{max} - \left(\frac{w_{max}-w_{min}}{T_{max}}\right) * (t) \tag{16}$$

where, r_1 *and* r_2 are random number between 0 to1. $w(t)$ represent adaptive inertia weight at iteration t, w_{max} value is set as 0.9 and w_{min} value is set as 0.4 respectively presenting maximum and minimum inertia weights. T_{max} represent maximum number of iterations. The $C_{1initial}$ is set as 0.07 and $C_{2initial}$ is set as 1.0 value.

Step 5: Apply the modified particle velocity and position strategy.

The update position and velocity in step 4 may violet the power balance constraint as shown in Eq. (8) and disturb the fitness function as shown in Eq. (12)-(13) respectively. In comparison to traditional PSO, the proposed M-PSO employed in this study integrates several enhancements to improve convergence and solution quality. First, an improvement factor dynamically adjusts the cognitive (C_1) and social (C_2) coefficients as presented in Eq. (17), thereby preventing premature convergence by encouraging diversification when improvement is observed.

$$improve = [\{P_{best}(t-1) - G_{best}(t-1)\}/P_{best}(t-1)] \tag{17}$$

If $improve > 0$, increase C_1 to encourage personal learning (diversification) and decrease C_2 (exploitation) as in Eqs. (18-19). I_{mf} is initially set as 0.1.

$$C_1(\mathrm{t}) = C_{1initial} * \left(1 + I_{mf} * improve\right) \tag{18}$$

$$C_2(\mathrm{t}) = C_{2initial} * \left(1 + I_{mf} * improve\right) \tag{19}$$

Otherwise, $improve \le 0$, C_1 and C_2 remain to the their initial values as follows:

$$C_1(\mathrm{t}) = C_{1initial};$$

$$C_2(\mathrm{t}) = C_{2initial}; \tag{20}$$

The velocity and position clamping regulate the search step size and maintain feasibility within boundaries as in Eqs. (21-22) respectively.

$$B^i{}_{(t)} = max\left(min\left(B^i{}_{(t)}\right), B^{imax}\right), B^{imin} \tag{21}$$

$$A^i{}_{(t)} = max\left(min\left(A^i{}_{(t)}\right), A^{imax}\right), A^{imin} \tag{22}$$

Finally, a velocity mirror effect is introduced as shown in Eq. (23) to handle boundary violations, ensuring that particles remain within the feasible search space without being discarded.

$$B^i{}_{(t)} = \begin{cases} -B^i{}_{(t)}, & if\ A^i{}_{(t)} \notin \left[A^{imax}, A^{imin}\right] \\ B^i{}_{(t)} & otherwise \end{cases} \tag{23}$$

Step 6: Update P_{best} and G_{best}

In this step, P_{best} value will be updated only when the current value improves upon the previous P_{best} otherwise it is remains unchanged. Subsequently, the G_{best} value will be updated based on the latest P_{best} values.

Step 7: Stop optimization.

A maximum iteration is applied for stopping criteria. If the maximum iteration is reached, the M-PSO algorithm will solve the ELD function for next hour data until the 24 hour and save the optimum results. Otherwise the algorithm returns to step 4.

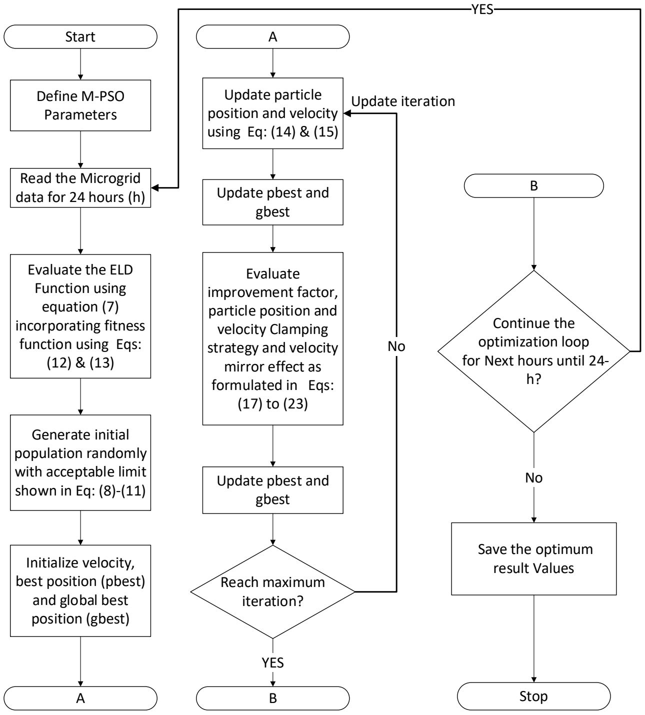


Figure 1 Flow chart of Proposed M-PSO Algorithm for Solving ELD Problem

4.0 RESULTS AND DISCUSSION

The proposed M-PSO algorithm was tested on the islanded MG system for ELD problems under two scenarios such as ELD problem with thermal generators and ELD problem with thermal generators, solar and wind units. The simulation study incorporating 30 different runs. The number of population and maximum iteration are set to 30 and 200 respectively. The MATLAB R2023b platform was utilized in 3.60 GHz core i7 processor with 8 GB RAM computer to perform simulation study.

The obtained results in term of F_{cost} (\$/h) and F_{CTotal} (\$/day) are compared with the results reported in existing studies including self-adaptive comprehensive differential evolution (SACDE) [17], reduced gradient method (RGM), ant colony optimization (ACO) method [18], cuckoo search algorithm (CSA), interior search algorithm (ISA) [19], krill herd (KH) algorithm [20] and whale optimization algorithm (WOA) [21].

4.1 Scenario-1: ELD Problem with Thermal Generator (ThG)

In this scenario, the microgrid with 3 thermal generator units considering PB and GL constraints are tested to solve ELD problem. The coefficient characteristics of ThG units are taken from [17]. Table 1 presents the hourly result obtained by proposed M-PSO in terms of power generated from ThG, F_{cost} (\$/h) and F_{CTotal}

($/day). The simulation result shows that, the optimal total cost obtained by M-PSO is $176166.185/day and the lowest achieved at hour-1.

Table 1 The optimal result obtained by M-PSO for the scenario-1

Hour	PD (MW)	Generating units (MW)			F_{Cost} ($/h)
		P1	P2	P3	M-PSO
1	140	37.749	45.306	56.944	6151.599
2	150	39.157	48.483	62.359	6380.488
3	155	42.288	49.509	63.203	6495.379
4	160	43.914	51.041	65.045	6610.779
5	165	44.836	52.858	67.306	6726.619
6	170	48.065	54.025	67.910	6842.808
7	175	48.980	55.351	70.669	6959.405
8	180	50.462	56.842	72.696	7076.427
9	210	60.422	65.433	84.145	7787.022
10	230	68.227	70.677	91.096	8268.822
11	240	71.184	73.550	95.266	8512.137
12	250	73.880	77.114	99.007	8757.115
13	240	71.006	73.400	95.593	8512.134
14	220	64.375	68.060	87.565	8027.103
15	200	57.700	61.765	80.536	7548.536
16	180	50.697	56.974	72.330	7076.425
17	170	47.410	54.099	68.491	6842.793
18	185	53.010	57.575	74.415	7193.850
19	200	57.098	62.544	80.358	7548.539
20	240	71.361	72.864	95.776	8512.142
21	225	65.790	69.103	90.108	8147.755
22	190	53.804	58.914	77.281	7311.697
23	160	44.320	51.800	63.880	6610.810
24	145	39.327	46.304	59.369	6265.798
F_{CTotal} ($/day)					**176166.185**

Therefore, to verify the effectiveness of proposed M-PSO, the obtained result in terms of covergence characterstic was compared against PSO algorithm (hour-1) as shown in Figure 2. The optimal results obtained obtained by M-PSO and PSO is slightly same for this small system without solar and wind power. It can be seen that both algorithms converges smoothly within the 20th iteration towards to optimal cost for hour-1.

The robustness characterstic comparision of proposed M-PSO versus PSO after 30 independent runs for the scenario-1 is shown in Figure 3. The proposed M-PSO achieved best cost, worst cost, average cost and standard deviation (std) of $6151.599/h, $6155.936/h, $6152.235/h and 0.969 respectively. Whereas, PSO achieved achieved best cost, worst cost, average cost and std of $6151.605/h, $6157.300/h, $6152.840/h and 1.230. Thus, it shows that M-PSO can provide consistent results with slightly lower cost as compared to PSO.

The total cost obtained by proposed M-PSO has been compared with PSO, SACDE [17], RGM [18], ACO [18], CSA [19], ISA [19] and KH algorithm [20] algorithms in Figure 4. The comparative analysis has confirmed that the proposed algorithm has slightly improved the total cost as compared to PSO for scenario-1. The proposed M-PSO also can provide the cost saving up to 0.6344% as compared to RMG method.

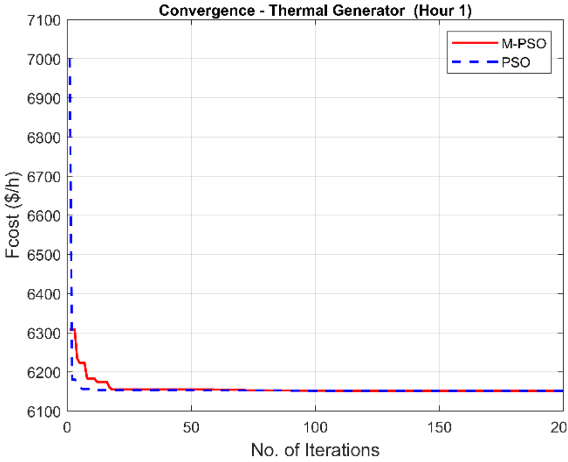


Figure 2 The convergence comparison of proposed M-PSO against PSO at hour-1 for scenario-1

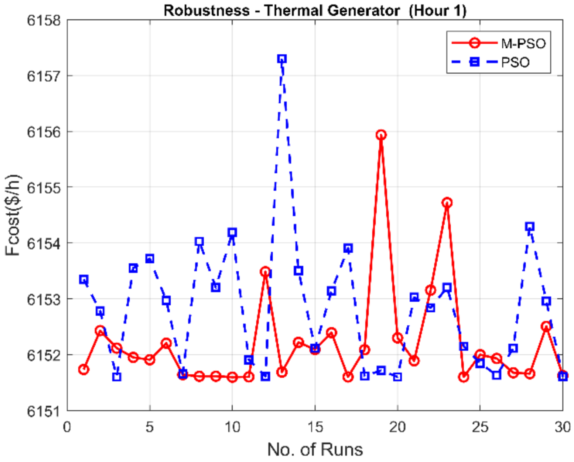


Figure 3 The robustness comparison of proposed M-PSO against PSO at hour-1 for scenario-1

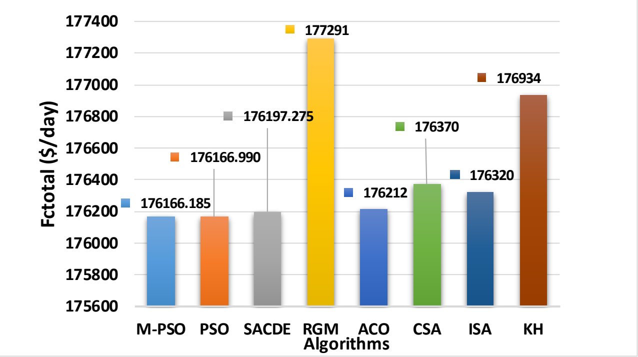


Figure 4 The comparison of F_{CTotal} ($/day) obtained by M-PSO and other algorithms

4.2 Scenario-2: ELD Problem with Thermal Generator, Solar and Wind Units

In this scenario, three ThG, one solar (PV) unit of 30MW and one wind unit of 40MW, with PB and GL constraints are considered for cost minimization by using proposed M-PSO. The 24 hours (h) power generation in megawatt (MW) of solar and wind units belong to a location on the east coast of the United States of America (USA) along with the hourly P_D are listed in Table 2 [22]. The cost shared by solar and wind generations are calculated by using Eq. (4) and Eq. (6) respectively [17].

Table 2 Hourly Based $P_D$and power generation from solar and wind units for the scenario-2

Hour	P_{solar} (MW)	P_{wind} (MW)	Hour	P_{solar} (MW)	P_{wind} (MW)
1	0	1.7	13	31.94	14.35
2	0	8.5	14	26.81	10.35
3	0	9.27	15	10.08	8.26
4	0	16.66	16	5.30	13.71
5	0	7.22	17	9.57	3.44
6	0.03	4.91	18	2.31	1.87
7	6.27	14.66	19	0	0.75
8	16.18	25.56	20	0	0.17
9	24.05	20.58	21	0	0.15
10	39.37	17.85	22	0	0.31
11	7.41	12.80	23	0	1.07
12	3.65	18.65	24	0	0.58

The optimal cost and power generated obtained by proposed M-PSO is shown in Table 3. The simulation result shows that, the optimal cost obtained by M-PSO is $166924.904/day. Where, the lower cost is $6102.138/h at hour-8.

Table 3 The optimal result obtained by M-PSO for the scenario-2

		Generating units (MW)			F_{Cost} ($/h)
Hour	PD (MW)	P1	P2	P3	M-PSO
1	140	37.000	45.151	56.149	6113.127
2	150	37.924	46.410	57.166	6187.127
3	155	39.871	46.965	58.895	6283.922
4	160	38.551	46.015	58.774	6230.398
5	165	43.348	50.364	64.068	6560.596
6	170	46.008	52.633	66.418	6728.746
7	175	41.375	49.674	63.022	6479.662
8	180	37.033	44.362	55.865	6102.138
9	210	46.062	52.716	66.592	6751.499
10	230	48.754	54.001	70.025	6931.894
11	240	64.682	67.291	87.817	8028.070
12	250	67.504	69.792	90.404	8217.942
13	240	55.962	60.851	76.897	7419.074
14	220	52.477	57.016	73.347	7159.352
15	200	51.419	57.505	72.736	7122.155
16	180	44.587	51.598	64.805	6638.684
17	170	43.060	50.280	63.649	6547.026
18	185	51.440	56.722	72.658	7097.204
19	200	57.177	61.968	80.105	7530.824
20	240	70.848	73.463	95.519	8508.013
21	225	66.419	69.941	88.491	8144.205
22	190	53.788	58.850	77.053	7304.422
23	160	43.791	51.025	64.114	6586.214
24	145	39.105	46.728	58.587	6252.609
F_{CTotal} ($/day)					**166924.904**

The convergence trajectories of the proposed M-PSO and PSO for scenario-2 under 200 iterations are illustrated in Figure 5. After iteration 21, it found that proposed M-PSO converged at $6102.138/h as compared to PSO at $6102.431/h. Thus, it shows the proposed algorithm can provide lower cost during the searching process.

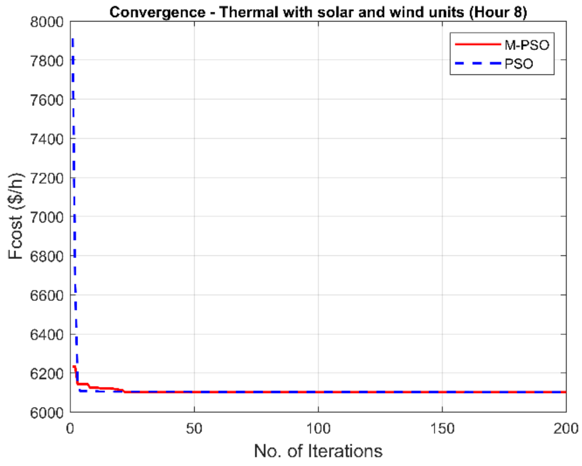


Figure 5 The convergence comparison of proposed M-PSO with PSO at hour-8 for scenario-2

The robustness performances of the proposed M-PSO and PSO after 30 independent runs for scenario-2 are presented in Figure 6. The proposed M-PSO achieved best cost, worst cost, average cost and std of $6102.138/h, $6103.577/h, $6102.583/h and 0.415 respectively. whereas, PSO achieved best cost, worst cost, average cost and std of $6102.431/h, $6106.301/h, $6103.279/h and 1.110 respectively. Small std of M-PSO shows the improvement of robustness of algorithm as compared to the PSO.

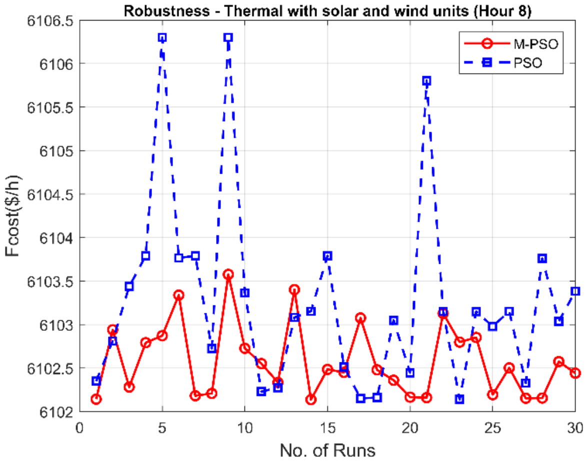


Figure 6 The convergence comparison of proposed M-PSO with Traditional PSO with respect to iteration at hour-8 for scenario-2

Furthermore, the total cost obtained by M-PSO is lower than PSO, SACDE [17], RGM [18], ACO [18], CSA [19], ISA [19], KH [20] and WOA [21] algorithms. as presented in Figure 7. The cost saving can be obtained by proposed algorithm is up to 9.0427% as compared to RGM.

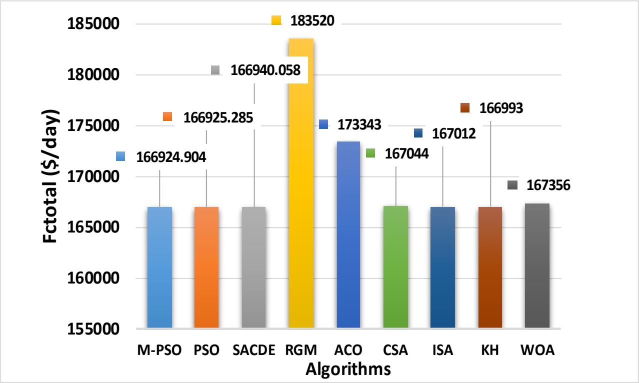


Figure 7 The comparison of F_{CTotal} ($/day) obtained by M-PSO and other algorithms

5.0 CONCLUSION

This study evaluates the performance of proposed M-PSO incorporating velocity and position clamping strategy for solving ELD problems in the islanded MG considering thermal and RE sources. This strategy enhances the exploration-exploitation balance of proposed M-PSO algorithm to converge more reliably in complex, constrained optimization problems. The simulation results show that the proposed M-PSO has significantly improved the F_{CTotal} up to 0.6344% as compared to RGM algorithm for scenario-1.

While scenario-2 highlighted the importance of RE sources integration when the proposed M-PSO can save up to 9.0427% as compared to RGM algorithm. The comparative analysis among both scenarios presents that the proposed M-PSO can provide significant cost saving of 5.2457% when considering the RE sources in the islanded microgrid as in scenario-2. Thus, the RE sources can support the P_D with lower cost and limits the usage of thermal generation. Meanwhile, the RE sources are also capable to reduce the greenhouse gas emission (GHG) to support the national policy of zero carbon. Therefore, the proposed M-PSO algorithm can be further evaluated to solve the ELD problem considering both cost and emission simultaneously.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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