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Research Article

The application of equilibrium optimizer for solving modern economic load dispatch problem considering renewable energies and multiple-fuel thermal units

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Abstract. This study presents a modern version of the economic load dispatch (MELD) problem with the contribution of renewable energies and conventional energy, including wind, solar and thermal power plants. In the study, reduction of electricity generation cost is the first priority, while the use of multiple fuels in the thermal power plant is considered in addition to the consideration of all constraints of power plants. Two meta-heuristic algorithms, one conventional and one recently published, including Particle swarm optimization (PSO) and Equilibrium optimizer (EO), are applied to determine the optimal solutions for MELD. A power system with ten thermal power plants using multiple fossil fuels, one wind power plant, and three solar power plants is utilized to evaluate the performance of both PSO and EO. Unlike other previous studies, this paper considers the MELD problem with the change of load demands over one day with 24 periods as a real power system. In addition, the power generated by both wind and solar power plants varies at each period. The results obtained by applying the two algorithms indicate that EO is completely superior to PSO, and the solutions found by EO can satisfy all constraints. Particularly in Case 1 with different load demand values, EO achieves better total electricity production cost (TEGC) than PSO by 0.75%, 0.87%, 0.13%, and 0.45% for the loads of 2400 MW, 2500 MW, 2600 MW and 2700 MW. Moreover, EO also provides a faster response capability over PSO through the four subcases although EO and PSO are run by the same selection of control parameters. In Case 2, the high efficiency provided by EO is still maintained, though the scale of the considered problem has been substantially enlarged. Specifically, EO can save $51.2 compared to PSO for the minimum TEGC. The savings cost is equal to 0.33% for the whole schedule of 24 hours. With these results, EO is acknowledged as a favourable search method for dealing with the MELD problem. Besides, this study also points out the difference in performance between a modern meta-heuristic algorithm (EO) and the classical one (PSO). The modern metaheuristic algorithm with special structure is highly valuable for complicated problem as MELD.

Keywords: Economic load dispatch; Particle swarm optimization; Equilibrium optimizer; multiple fuels; thermal generator; renewable energies.

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1. Introduction

Economic load dispatch (ELD) is considered one of the most crucial problems in power system operation. The determination of an optimal solution to ELD allows the operators to save more operation cost and reduce environmental damage (Xiang *et al.*, 2021). Nowadays, the concept of the conventional economic load dispatch (CELD) is obsoleted and does not fit modern power systems anymore because of its static nature. In addition, CELD only considers thermal generators as the sole generating source. However, the modern economic load dispatch (MELD) was updated once multiple objective functions and renewable energy sources (RES) (Zhang *et al.*, 2021; Shen *et al.*, 2019; Li *et al.*, 2020) were taken into account. Specifically, several objective functions can be listed, such as reducing the total electricity generating cost (TEGC), reducing the entire emissions (REE), etc. These objectives can be considered simultaneously or separately, depending on the different targets such as financial factor or/and technical factor. Besides, both CELD and MELD have a lot in common, such as the set of related constraints and the type of variable needed to be found. In terms of related constraints, several typical constraints can be named, such as the power balance constraint, the generator operational constraints, the multiple fuel constraint, etc. About the types of variables when dealing with both CELD and MELD problems, there are two of them, including the control and the dependent variables. These variables must be defined prior to any kind of computation. Particularly with these mentioned problems, control variables are the power generated by all the existent generators in the system except for the first generator, which is considered the dependent variable. In the whole process of solving such CELD and MELD problems, an optimal solution is acknowledged if only both control variables and dependent variables satisfy all the related constraints with the minimum value of the fitness function. The types of RES integrated with power systems are mainly solar and wind energies. Therefore, the thermal, wind and solar power plants supply enough power to loads in MELD, while only thermal power plants are in charge of the role in CELD (Hlalele *et al.*, 2021; Kim and Kim, 2020). In

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this study, MELD problem with the integration of RES into thermal power plants is solved.

At the beginning of the foundation for the CELD problem, the solution for the problem is commonly given by the old fashion computing methods such as the gradient method, the quadratic method, and the conventional iterative method. The real efficiency of these methods seems to be good and acceptable as the theorem study. However, at the time, MELD is widely studied and the scale of the problem is enlarged so much over CELD. Besides, many complicate constraints are also taken into account. As a result, the whole complicated degree of MELD is increased substantially. The application of old fashion computing methods begins showing more drawbacks such as a low response, a poor accuracy. Luckily, in two past decades, computing methods have witnessed a huge leap forward in meta-heuristic methods to cope with high-degree complicated problems. There have been a huge number of meta-heuristic applied to MELD problem, such as Genetic algorithm (GA) (Chen and Chang, 1995), Particle swarm optimization (PSO) (Park *et al.*, 2005), Artificial algae algorithm (AAA) (Kumar and Dhillon, 2018), Modified differential evolution (MDE) (Nguyen *et al.*, 2018), Grey wolf optimal (Pradhan *et al.*, 2016), Tunicate Swarm Optimizer (TSO) in (Hien *et al.*, 2021), differential evolution (DE) in (Parouha and Das, 2018), improved firework algorithm (IFA) (Zare *et al.*, 2021), quantum PSO (QPSO) (Xin-gang *et al.*, 2020), improved Manta ray optimization (IMRO) (Hassan *et al.*, 2021), simplex search-based PSO (SSM-PSO) (Chopra *et al.*, 2021), improved bird swarm optimization (IBSO) (Fu *et al.*, 2020), Distributed roust optimization (DRO) (Chang *et al.*, 2021), hybrid grey wolf optimizer (Al-Betar *et al.*, 2020), Pattern search and Sequential quadratic programing-based genetic algorithm (PS-SQP-GA) (Alsumait *et al.*, 2010), Double weight-based PSO (DW-PSO) (Kheshti *et al.*, 2018), improved bacterial foraging algorithm (IBFA) (Pandit *et al.*, 2012), acceleration coefficients-based PSO (AC-PSO) (Ghasemi *et al.*, 2019), Nondominated sorting-based genetic algorithm (NSGA) (Basu, 2008), Chaotic differential evolution (CDE) (Coelho and Mariani, 2006), biogeography optimization (BO) (Xiong and Shi, 2018), and Ameliorated dragonfly algorithm (ADA) (Suresh *et al.*, 2019). These algorithms have shown a good performance as compared to deterministic algorithms based on Lagrange relaxation, newton, gradient search (Vaisakh and Reddy, 2013; Nguyen *et al.*, 2019); however, these algorithms have not been applied to deal with the complex fuel cost functions of thermal units with three fuel options (Chen *et al.*, 2020; Pham *et al.*, 2022). Multiple fuel options can be used for generating units in thermal power plants and the different options can bring more benefits to thermal power plants. But the units with several fuel options can bring more challenges to optimization tools since the generation of unit is not continuous within allowable ranges (Dieu *et al.*, 2013; Jeyakumar *et al.*, 2006). Almost applied algorithms for the multiple fuel units are strong and not much dependent on Lagrange function, excluding augmented Lagrange Hopfield network (ALHN) (Dieu *et al.*, 2013). In fact, these applied methods are comprised of Modified PSO (Jeyakumar *et al.*, 2006), Differential evolution (Noman and Iba, 2008), Self-Adaptive Differential Evolution (SDE) (Balamurugan and Subramanian, 2007), adaptive real coded genetic algorithm (ARC-GA) (Amjady and Nasiri-Rad, 2010), and Improved evolutionary programming (IEP) (Park *et al.*, 1998). These algorithms have reported good results with minimum fuel cost and high stable search ability; however, the search speed was almost neglected once the comparison of setting parameters was not implemented.

In this study, the original version of PSO (Kennedy and Eberhart, 1995) and one modern meta-heuristic algorithm called Equilibrium optimizer (EO) (Faramarzi *et al.*, 2020) are applied to determine the optimal solution for MELD with multiple fuel options and renewable energies. The multiple fuel options are examined in the operation cost function belonging to thermal generators. The renewable generating sources, including one wind farm and three solar power plants, and the variation of power output values from these sources within 24 hours are included. The first priority of this study is to reduce the total operation cost as much as possible. The application of both EO and PSO is considered to be a good example for evaluating the performance of a modern meta-heuristic algorithm and a classical algorithm.

Briefly, the novelties of this study can be seen on different aspects, including proposing the MELD problem where varied load demands are employed with a day and the 24-single periods, the variation of power generated from both wind and solar power plants is examined throughout the 24 periods, and the difference in raw performance between the modern meta-heuristic algorithm and the classical one is clarified and pointed out based on the results. The key contributions of the study are stated in the four claims. Firstly, the proposed MELD is successfully solved considering the presence of both solar and wind power plants. Secondly, the optimal solution for MELD is determined under the consideration of the multiple fuel constraints. Thirdly, EO is proved to be the best applied method for the proposed problem through the comparisons of the results reached by PSO and other previous studies. Lastly, the superiority of a modern meta-heuristic algorithm (EO) over the classical one (PSO) is proved and demonstrated by results and figures.

In this study, two power systems with different complicated levels are considered for reaching the objective function of reducing the total electric generation cost over optimal schedule horizon, one hour for the first system and 24 hours for the second system. The two systems use the same ten thermal generating units in which each thermal generating unit can use two or three fuel types for electric production. The total cost values from the two systems are comparison criteria to evaluating the performance of EO and other algorithms.

2. Problem descriptions.

2.1 Main objective function

As mentioned earlier, there are three types of generating sources in this study, including thermal power plants, wind power plants, and solar power plants. However, only the operation process of thermal generators consumes fossil fuels. So, the major target of the problem is to reduce the total electricity generation cost (TEGC) from thermal power plants. The target can be formulated as follows.

$$Reducing\ TEGC = \sum_{g=1}^{G} EGC_g \tag{1}$$

Where EGC_g (\$/h) is the fuel cost of the *gth* thermal generator and formulated by (Park *et al.*, 2005):

$$EGC_g = \varepsilon_g + \delta_g PG_g + \gamma_g PG_g^2\ with\ g = 1, \dots, G \tag{2}$$

$TEGC$ is the total fuel cost of all G generators working in one hour meanwhile EGC_g is the fuel cost of one generator only. So, the unit of TEGC is \$ but that is \$/h for EGC_g. The cost function of the thermal generator, EGC_gdescribed in Equation (2) is depicted at Fig.1a.

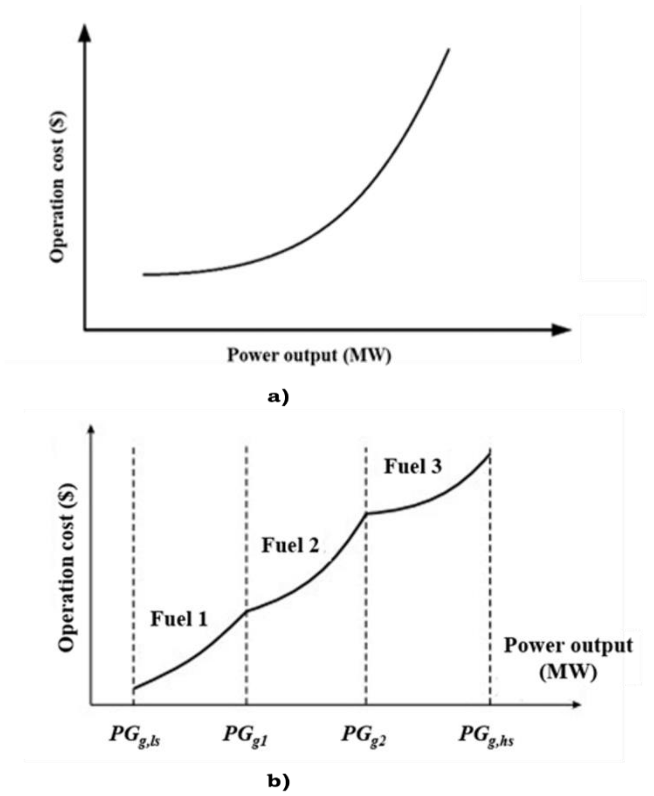

Fig. 1 Models of fuel cost function for thermal units: a) One fuel option; b) multiple fuel options

In addition, the multiple fuels aspect is also considered in this study, as shown in Fig. 1b. According to (Dieu *et al.*, 2013), The mathematical expression of EGC_g is represented by:

$$EGC_g = \begin{cases} \varepsilon_{g1} + \delta_{g1} PG_g + \gamma_{g1} PG_g^2, & fuel\ 1, PG_{g1,ls} \le PG_g \le PG_{g1,hs} \\ \varepsilon_{g2} + \delta_{g2} PG_g + \gamma_{g2} PG_g^2, & fuel\ 2, PG_{g2,ls} \le PG_g \le PG_{g2,hs} \\ & \ldots \\ \varepsilon_{gw} + \delta_{gw} PG_g + \gamma_{gw} PG_g^2, & fuel\ w, PG_{gw,ls} \le PG_g \le PG_{gw,hs} \end{cases} \quad (3)$$

Where ε_{g1}, δ_{g1}, and γ_{g1} are fuel consumption factors while using fuel 1 of generator g; $PG_{g1,ls}$ and $PG_{g1,hs}$ are the lowest and highest power generated by generator g whilst using fuel 1. Similarly, ε_{g2}, δ_{g2} and γ_{g2} are fuel consumption factors of generator g whilst using fuel 2. $PG_{g2,ls}$ and $PG_{g2,hs}$ are the lowest and highest power generated by generator g whilst using the fuel 2. Finally, ε_{gw}, δ_{gw}, and γ_{gw} are fuel consumption factors while using the fuel w of generator g; and $PG_{gw,ls}$ and $PG_{gw,hs}$ are the lowest and highest power generated by generator g whilst using the fuel w.

2.2 Constraints

There are important constraints that must be respected while solving both CELD and MELD. They are described one by one as follows:

- Power balance constraint: This constraint is mainly about the relationship between the generating side and the demand side. According to (Duong *et al.*, 2021), the mathematical expression of the constraint is presented by Eq 4:

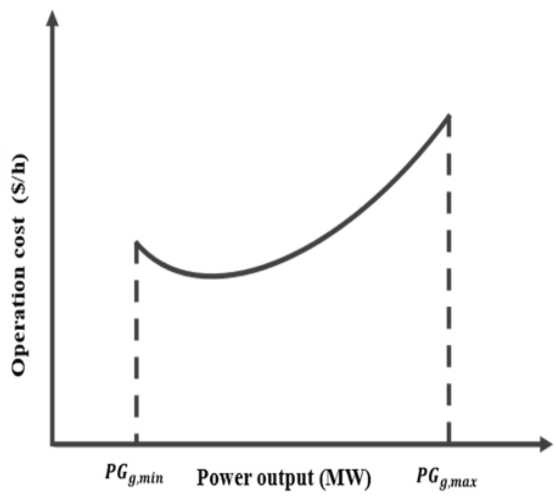

Fig. 2 The working limitation of a thermal generator

$$PD + PL = \sum_{g=1}^{G} PG_g + PW + PS \quad (4)$$

In Equation (4), PL is calculated by using the Equation (5) below (Dieu *et al.*, 2013):

$$PL = \sum_{g=1}^{G} \sum_{h=1}^{G} PG_g B_{gh} PG_h + \sum_{g=1}^{G} B_{0g} PG_g + B_{00} \quad (5)$$

- Generator operational constraints: This constraint is about the working limit belonging to thermal generators. That means power output must allocate in the allowed range as depicted in Equation (6). Besides, the working limitation of a typical thermal generator is illustrated in Fig. 2. According to (Dieu *et al.*, 2013), this constraint is formulated as follow:

$$PG_{g,min} \le PG_g \le PG_{g,max} \quad (6)$$

- The electricity producing constraint of solar power plant**:** according to (Phan et al., 2021) the power generated by solar power plant is limited as follows:

$$\sum_{q}^{N_S} P_{SG,q} \le 80\% \times PD \quad (7)$$

$$P_{SG,q}^{min} \le |P_{SG,q}| \le P_{SG,q}^{max} \quad (8)$$

3. The applied methods

To determine the optimal solution for MELD in this study, two meta-heuristic methods, Particle swarm optimization (PSO) (Kennedy and Eberhart, 1995) and Equilibrium optimizer (EO) (Faramarzi *et al.*, 2020) are applied to solve the given problem. PSO is inspired by the foraging practice of animal swarms in real life such as fish, bird, ox, etc., while EO is inspired by physical law named equilibrium state of mass. The key difference between PSO and EO is their update process for new solutions, which will be described in the following subsections:

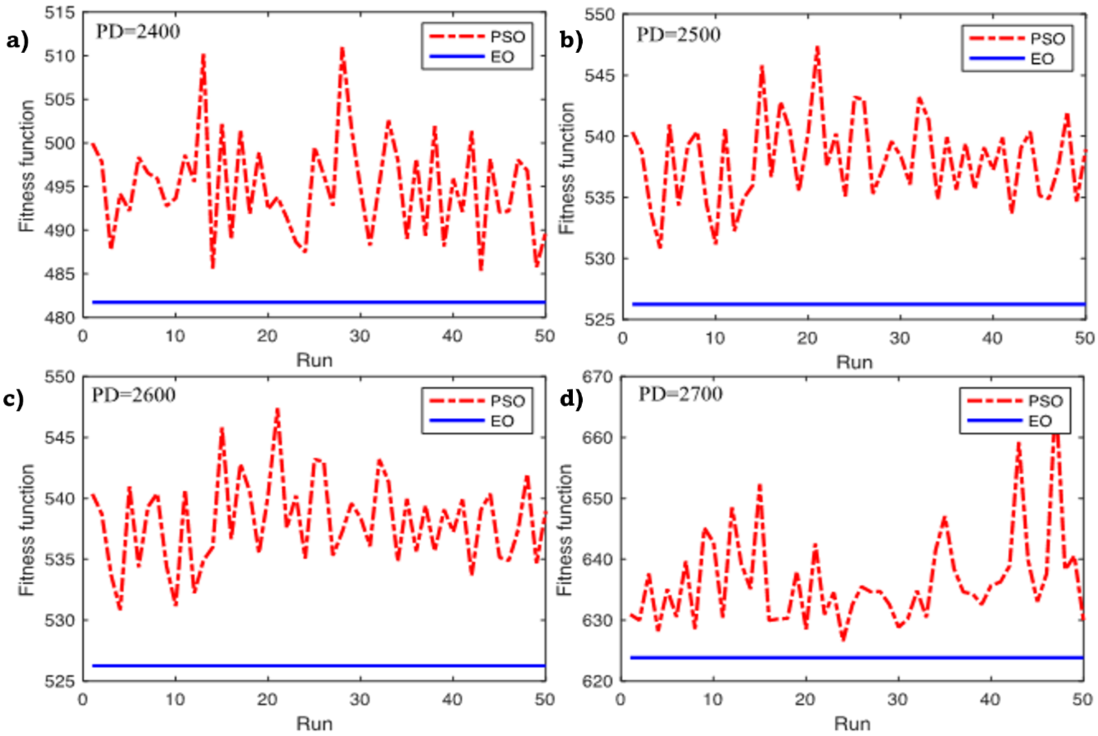

Fig. 3 The results obtained by PSO and EO after 50 independent runs corresponding to different load demand values: a) Load of 2400MW, b) Load of 2500MW, c) Load of 2600MW, and d) Load of 2700MW

3.1 The original version of PSO

The update process for new solutions belonging to PSO includes two main steps: the velocity update and the new position update. These steps are clarified by mathematical Equations (9) and (10) as follows:

$$V_i^{new} = V_i + cq_1 \times \gamma_1 \times (P_{Best,i} - P_i) + cq_2 \times \gamma_2 \times (P_{Gbest,i} - P_i) \quad (9)$$

$$P_i^{new} = P_i + V_i^{new} \quad (10)$$

3.2 The Equilibrium optimizer (EO)

The update process of EO is conducted based on the references around the four best solutions at each iteration. The key elements of the whole process are described as follows:

$$S_i^{new} = S_s + (S_i - S_s)Ex + \frac{Ge}{vr}(1 - Ex) \quad with\ i = 1, \dots, NP \quad (11)$$

In Equation (11), the exponential term (*Ex*) and the generation rate (*Ge*) are calculated by using the Equations below:

$$Ex = \theta_1 sign(\omega - 0.5)(e^{-tf.vr} - 1) \quad (12)$$

Where θ_1 is set by 2, and the integer number (ω) is a random value between 0 and 1. Besides, the time length factor (tf) is a value that changes with each iteration, and its value depends entirely on the maximum iteration number (It^{Max}) and the current iteration number (It). tf can be determined by using the Equation (13)

$$tf = \left(1 - \frac{H}{H^{Max}}\right)^{\theta_2\left(\frac{H}{H^{Max}}\right)} \quad (13)$$

where β_2 is set by 1 (Faramarzi *et al.*, 2020), H is the current iteration, and H^{Max} is the maximum quantity of iteration.

About the generation rate (*Ge*), this term can be found by using the Equation (14) below:

$$Ge = Ex.\delta.(S_s - vr.S_i) \quad (14)$$

Where,

$$\delta = \begin{cases} \frac{rd_3}{2} & if\ rd_4 \geq cf \\ 0 & else \end{cases} \quad (15)$$

Where $\boldsymbol{cf}$ is set by 0.5 (Faramarzi *et al.*, 2020).

4. Results and discussions

The study is conducted on a personal computer with a Central processing unit (CPU) of 2.0 GHz and 8 GB of Random-Access Memory (RAM). The coding is implemented in MATLAB software with version 2018b. The two study cases are implemented as follows:

- Study Case 1: The system with ten thermal units using multiple fuels for four load demand cases, including 2400, 2500, 2600, and 2700 MW. Data of the system is taken from (Park *et al.*, 1998).
- Study Case 2: One wind and three solar photovoltaic power plants are integrated into the above ten-unit system. The power output supplied by wind farms and solar power plants over one day are taken from the studies (Zhang *et al.*, 2017) and (Augusteen *et al.*, 2016), respectively.

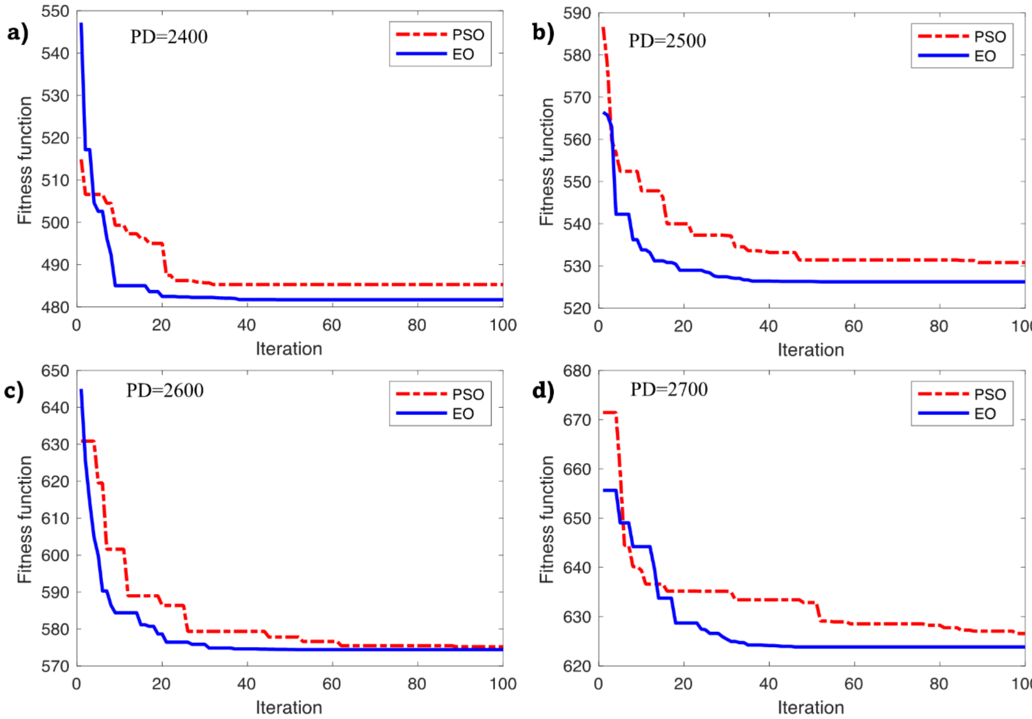

Fig. 4 The best convergences obtained by PSO and EO among 50 independent runs corresponding to different load demand values: a) Load of 2400MW, b) Load of 2500MW, c) Load of 2600MW, and d) Load of 2700MW

4.1 The determination of population and maximum iteration

Initially, the determination of optimal settings for the initial control parameters, including population and maximum iteration, is one of the first hurdles that must be overcome. To deal with the first hurdle, different simulations have been conducted before the certain values for the population and the maximum number of iterations are established. Due to the high complexity posted by the set of constraints, the large scale of search space explicitly seen in Case 2, and the non-convex characteristic of both CELD and MELD, EO and PSO are executed with different settings of population and maximum iteration. For Study Case 1, the population is set to 30, 40, 50, and 60, respectively. The maximum iteration is also varied from 80, 90, 100, and 150, respectively. The results obtained by all experiments revealed that the value of the population strongly influences the quality of the solutions and the execution time of each iteration, while the iteration number highly involves the quality of the solutions and the execution time of an independent run. As a result, when the population is set to a high value, the quality of the solutions will be improved; however, each iteration will require more time to complete. If maximum iteration is fixed at a high value, the quality of the solution at the end of each independent run could be enhanced, but more time would be consumed to finish a run. More importantly, if both population and maximum iteration are set to large values, the applied methods will result in the same optimal solutions after a long execution time. In that circumstance, the performance of the two applied methods cannot be evaluated precisely and reliably. By analysing the results obtained by the mentioned experiments, 50 and 100 are considered the optimal setting for population and maximum iteration. These settings also perfectly serve the initial purpose of evaluating the performance of the EO and PSO. Study Case 2 is more complicated than Study Case 1 by considering 24 periods instead of one period. The setting of Case 1 is applied for each hour of Case 2. So, Case 2 takes more simulation time than Case 1 as a result.

4.2 Results of Case 1

Fig. 3 presents the results obtained by PSO and EO for 50 trial runs. The four subfigures have the same characteristic that EO can reach approximately the same solution for over 50 runs but those from PSO highly fluctuate. In addition, PSO cannot reach the same best solution as EO. Fig. 4 shows the best run of PSO and EO for the four cases. Specifically, for the first load demand case with 2400 MW, EO only needs over 50 iterations to reach the best value of the considered fitness function, while PSO cannot perform the same even if the last iteration is used on this best run. For the last three cases of load demand, EO still maintains its fast-response capability over PSO by reaching the fitness value with fewer iterations. Particularly, with load demands of 2500, 2600, and 2700 (MW), EO also requires approximately 60 iterations to obtain the best value, while PSO cannot achieve any similar value on the three comparisons. Clearly, EO is much faster than PSO in finding the most optimal generation solutions.

Fig. 5 shows the best cost for the four cases obtained by PSO, EO and other methods. In the figure, PSO is the worst method while EO can reach the same or slightly smaller cost than others. It should be emphasized here that EO only search solution by using 50 and 100 for population and iterations, whereas others must use higher than 100 for iterations excluding ALHN (Dieu *et al.*, 2013), which is a deterministic algorithm. Because of this evidence, the superiority of EO over other previous methods is not deniable, so this study focuses on analyzing the efficiency of EO and PSO for each subfigure corresponding to each level of load demand. Particularly, in the first case of load demand in Fig. 5 with 2400 MW, the TEGC achieved by EO is only $481.723, while the similar value obtained by PSO is up to $485.317. The savings cost saved by EO over PSO in this case is approximately $3.6, corresponding to 0.75%. On the three remaining load demand levels, the TGEC values achieved by EO are, respectively, $526.239, $574.381, and $623.809. The similar values resulted by PSO are,

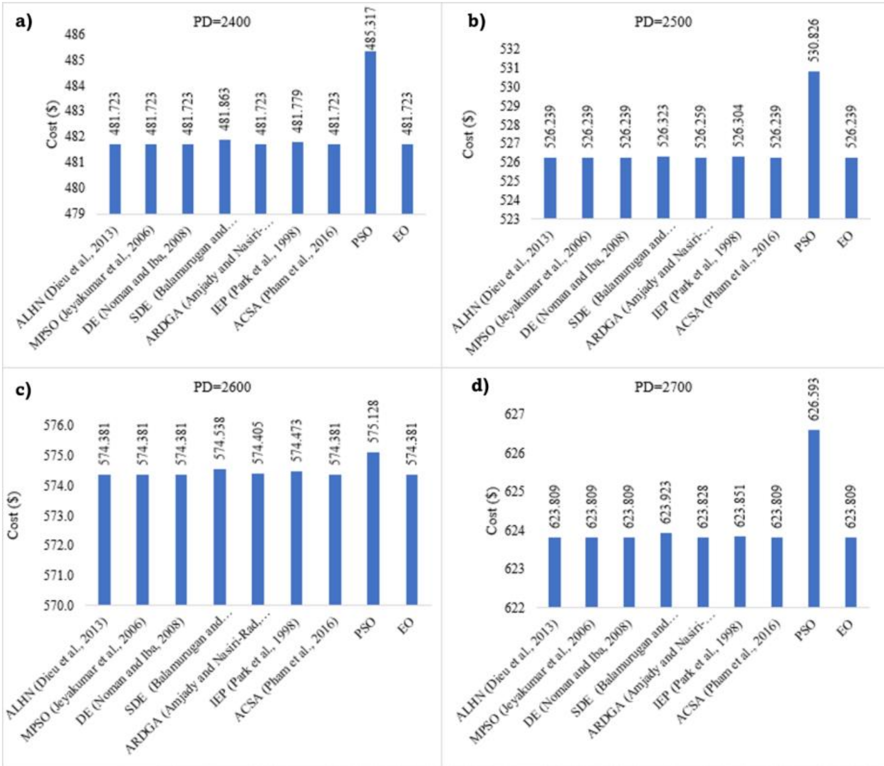

Fig. 5 The comparison between two applied methods and other methods on different values of load demand: : a) Load of 2400MW, b) Load of 2500MW, c) Load of 2600MW, and d) Load of 2700MW

respectively, \$530.826, \$575.128, and \$626.259. The savings costs saved by EO over PSO in these cases are \$4.587, \$0.747, and \$2.784, corresponding to 0.87%, 0.13%, and 0.45%, respectively. As stated in the study (Nguyen *et al.*, 2021), a method with better minimum, mean and maximum objective function is more effective than others. So, EO is more suitable than PSO for the system.

4.3 The results of Case 2

In the study case, the integrated system supplies electricity to loads over 24 hours as shown in Fig. 6. In addition, the generation of the wind and solar photovoltaic power plants are also given in Fig. 6. Both PSO and EO are applied to determine the optimal generation of the ten thermal generators and the summary of 50 runs is given in Fig. 7. In the figure, three comparison criteria are employed to analyse the efficiency of the two applied methods while dealing with the larger scale of the MELD problem, including the Minimum TEGC within 24 hours (Minimum), Average TEGC within 24 hours (Average), and Maximum TEGC within 24 hours (Maximum). The green bars stand for the results obtained by PSO, while the blue ones represent the similar values achieved by EO. For the first criterion, EO achieves \$15384.5 of the TEGC, while that of PSO is \$15435.7. It is easy to figure out that EO has saved \$51.2, or 0.33%, over PSO on this criterion in an operation day. Next, in

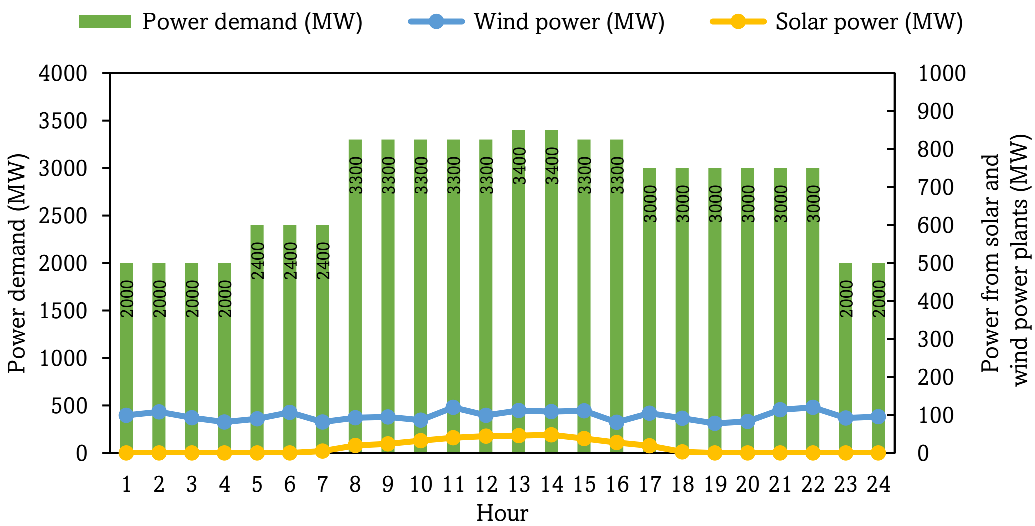

Fig. 6 Load demand and generation of wind and solar plants over 24 hours

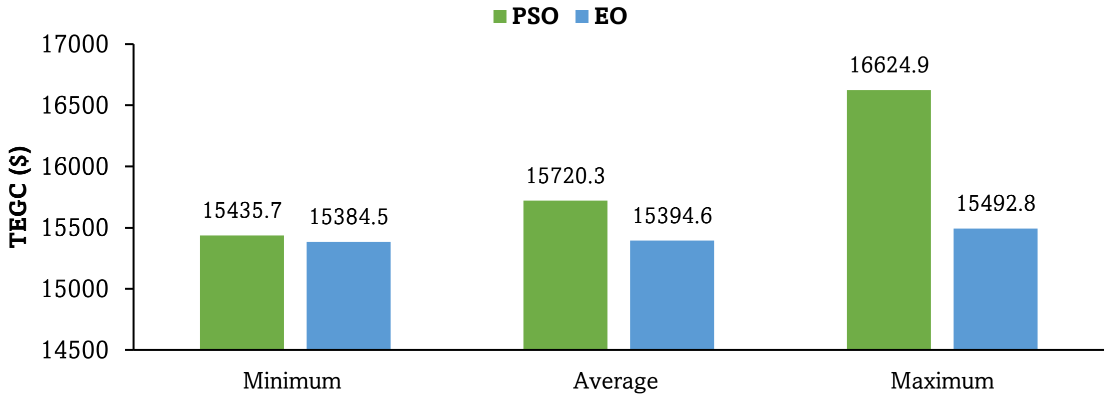

Fig. 7 Summary of 50 runs found by PSO and EO

the average and maximum criteria, the savings costs saved by EO over PSO are even larger. Specifically, the savings costs in these criteria are $325.7 and $1132.1, corresponding to 2.12% and 7.31%, respectively. Clearly, EO completely outperforms PSO while dealing with the large-scale MELD.

Fig. 8 shows the fuel cost at each hour for the best, mean, and worst solutions of over 50 solutions obtained by PSO and EO, corresponding with the subfigures a, b, and c. In terms of the best solution presented in Fig. 8a, EO always offers a better value of TEGC per hour. Particularly, regardless of the variation in load demand within 24 hours, the TEGC values found by EO at each hour are lower than the ones obtained by PSO at the same time. However, the differences between the TEGC values resulting from EO compared to the similar ones belonging to

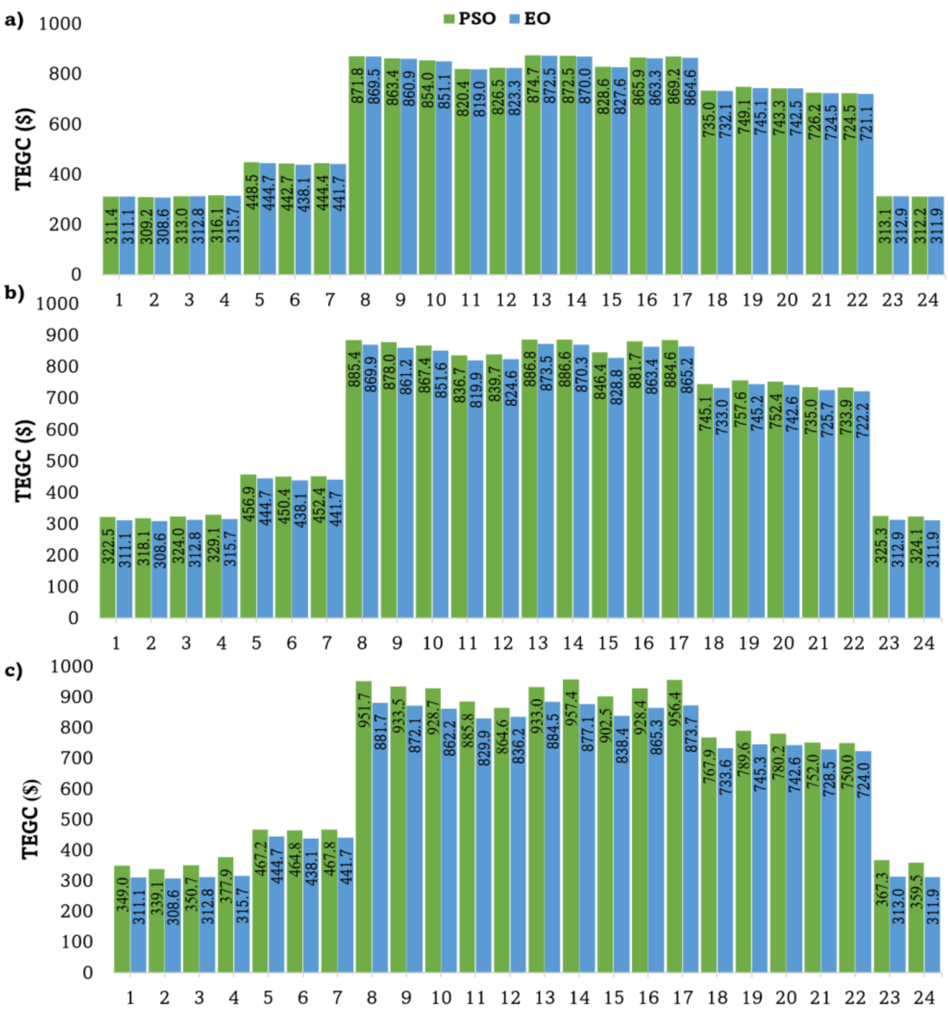

Fig. 8 The TEGC of each hour obtained by PSO and EO: a) TEGC of the best run, b) TEGC of the mean run, c) TEGC of the worst run

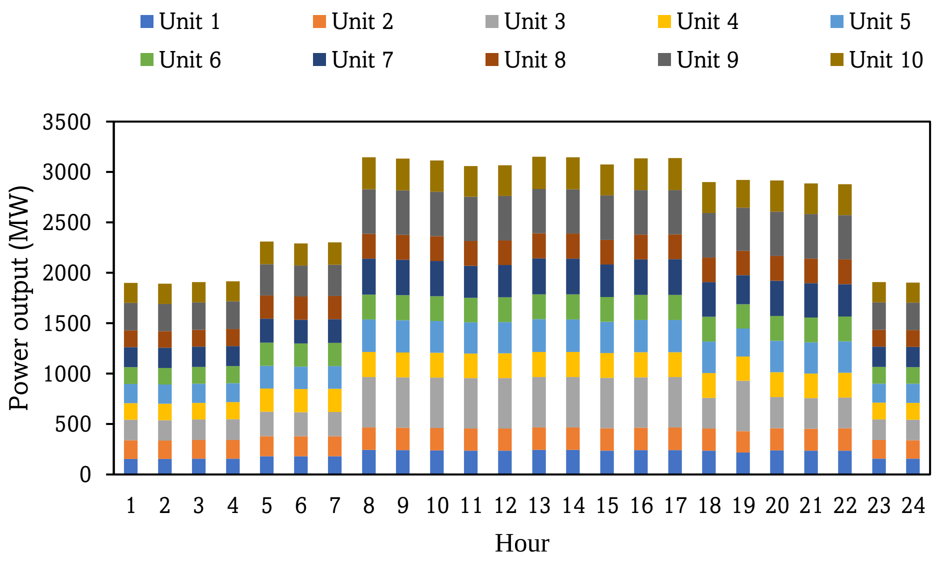

Fig. 9 The most optimal generations of each thermal unit over 24 hours

PSO are not much in Fig. 8a. Hence, the outstanding characteristics of EO over PSO are not clearly shown. In Fig. 8b, the efficiency of a modern meta-heuristic algorithm such as EO starts to reveal itself. In the figure, the contrast in TEGC values obtained by EO and PSO starts to depart from each other in all hours and is easy to observe. EO always results in lower values of TEGC over PSO throughout the 24 hours. Noticeably, the TEGCs found by EO are always better than PSO even in the high load demand hours. Finally, the observations on Fig. 8c indicate that the high efficiency of EO is enhanced when compared to PSO. Particularly, the better degree of TEGC values resulted by EO can be seen vividly for 24 hours, regardless of high demand hours or low demand ones. In addition to that, the TEGC values from 8 to 17 hours found by EO compared PSO are substantially better than the same period as mentioned in Fig. 8b.

The most optimal generations for the ten thermal units corresponding to the best solution are reported in Fig. 9. In general, the generation rate of the units is dependent on the load level at each hour and units with higher generation is more effective than units with lower generation.

4.3 Discussion on performance of EO and on renewable energies

EO is a metaheuristic algorithm mainly based on randomization, exploitation, and exploration. Randomization is a general characteristic for approximately all algorithms belonging to the metaheuristic family. So, EO as well as PSO are sensitive to settings of population, iterations and run number, leading to different results for the number of trials. Because of the unexpected characteristic, EO has been implemented for 50 trials for each study case to summarize the best, mean and worst results for comparisons. Fig. 4 above indicates the very stable ability of EO in reaching the best solution for four study cases. EO found the same solution quality for the 50 runs, which can be seen via the line of fuel cost, meanwhile PSO must suffer very high fluctuation among the 50 runs, especially the deviation between the best and the worst runs. The two algorithms were tested by using the same population of 50 and the same iteration of 100. About the structure, EO only use one main Equation (11) to update solutions, here they are generation of thermal units. PSO has updated velocity and location in which velocity is equivalent to an increased interval and location is solution. The algorithms have the same characteristic of using randomization, but EO almost do not have sensitivity to the randomization. Here, the setting of population and iteration are 50 and 100, not having enough impact on the change of EO but they highly influence the fluctuations of PSO. As compared to other previous algorithms shown in previous studies, the best performance of EO cannot be shown in terms of reaching less fuel costs than these algorithms. EO only reached smaller cost than several algorithms such as SDE, IEP, and ARDGA. Other algorithms did not show all simulated results as the study, so the full comparison is impossible to carry out. On the other hand, presentation of settings of iterations and population was not done in the studies too. However, the use of 50 and 100 for population and iteration is not high setting for the algorithm. And the comparison with PSO is the evidence for this statement. PSO could not reach the best solution although it was run 50 trials. So, EO is a very effective algorithm for this research.

In the second case of testing EO performance, the supplied power to load over 24 hours with an additional supply from solar and wind power plants are both employed. The second case is much more complicated than the first case in terms of multiple hours and the presence of renewable energies-based generating units. The uncertainty of wind and solar have not been considered, and this is the major shortcoming of the study. However, the power sources have a high contribution to form a load curve for one day within 24 hours and reduce the fuel cost from thermal units. The fixed power of the renewable energies-based units can guarantee energy security, i.e., load demand can be satisfied all hours. However, there are other cases that the real power of renewable power plants is smaller than predetermined values. This case is serious for the power system and frequency can be reduced to a smaller value than rated frequency. For this case, thermal units or battery energy storage system (BESS) as considered by (Kheiter *et al.*, 2022) can supply more power to compensate for the lack of the renewable energies-based units. To reach the purpose, BESS must save enough energy for discharge meanwhile the thermal units copes with the challenge of increasing power or starting up shut down units. This unexpected issue should be solved in the future work and the power system will become more effective in the future. Besides, the uncertainties and the mathematical models of renewable energy sources, including solar and wind power plants, as considered in (Kaur *et al.*, 2021; Khamharnphol *et al.*, 2022), should be employed while solving the MELD problem as another complex constraint for assessing the efficiency of a modern meta-heuristic algorithm such as EO. This implementation is also a great method to improve the overall quality of the study and make it closer to practice, where the penetration rate of these sources is growing.

5. Conclusion

In this study, one conventional ten-thermal unit power system and one integrated ten-thermal unit, three-solar photovoltaic plant and one wind-plant power systems are successfully solved by conventional meta-heuristic algorithm, named Particle swarm optimization and a modern one, named Equilibrium Optimizer. The evaluation of results about the minimum and maximum total electricity generating cost values indicated that EO is completely superior to PSO. Specifically, EO provides a quick response capability, lower fluctuations of fitness values for fifty independent runs, and fast convergence to optimal results. Therefore, EO has been acknowledged as a highly effective method for solving MELD problems. In the future, the MELD should be expanded with the consideration of higher-degree complicated constraints such as prohibited operation zone, valve point effects and uncertainties of renewable.
In addition to highly valuable contributions above, this study also copes with the following shortcomings:

- Other constraints of thermal generating units are still not evaluated on this study such as valve point effects, ramp-rate limits, prohibited zones, etc.
- The study only considers the case that both wind and solar power plants generate enough power to meet the demand as predicted. For other cases with a mismatch between the power generated by wind and solar power plants and the load demand, the evaluation in these cases is not taken place. As a result, no actions are proposed to deal with these scenarios while power from wind and solar power plants is lower or higher than load demand.
- The uncertainties of the wind and solar power plants is not clearly discussed and evaluated strictly.

By fully acknowledging the shortcomings, there are many improvements that must be conducted in the future.

- More high-complex constraints related to MELD must be taken into account.
- The uncertainties of power generated by wind and solar power plants must be fully evaluated while solving MELD.
- More scenarios of power system operation must be employed and analyzed. Especially, as there is a mismatch between the forecast and the real power production from wind and solar power plants. Consequences as well as solutions for the cases have to be calculated and proposed to reach the least impact.

Nomenclature

G	The number of thermal generators
ε_g, δ_g, and γ_g	The fuel coefficients
PG_g	The power output of thermal generator g (MW)
PD	The power demand required by the load (MW)
PL	The total power loss of the transmission process (MW)
$\sum_{g=1}^{G} P_g$	The total power generated by all thermal generators (MW)
PW and PS	The power supplied by wind and solar generators (MW)
B_{gh}, B_{0g}, and B_{00}	The loss factors
PG_g and PG_h	The power injected by the generators g and h (MW)
$PG_{g,min}$ and $PG_{g,max}$	The working limitations of generator g (MW)
$\sum_q^{N_s} P_{SG,q}$	The total power generated by all solar power plants (MW)
$P_{SG,q}$(MW)	Active power generated by solar power plant q (MW)
$P_{SG,q}^{min}$ and $P_{SG,q}^{max}$	The minimum and maximum power generated by solar generator q (MW)
NP	The population number
V_i^{new} and P_i^{new}	The new velocity and new position of the individual i.
V_i and P_i	The current velocity and current position of individual i
qc_1 and cq_2	The accelerating factors
γ_1 and γ_2	The random numbers in the interval between 0 and 1
$P_{Best,i}$ and $P_{Gbest,i}$	The best position at the time considered and the best position at all times of the individual i.
vr	A random value in the range of (0, 1)
rd_3 and rd_4	The random values in the interval between 0 and 1
cf	The comparative factor

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