# Economic Load Dispatch for Multiple Fuels and Solar Energy-Based Generating Units

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ABSTRACT

This study proposes a modified differential evolution algorithm (MDE) to determine the most optimal solutions to an economic load dispatch (ELD) problem. The problem takes into different selections of fossil fuel to run thermal generating units (TGUs) and the additional generation from solar photovoltaic generating units (SPGUs) so that the total generation cost (TGC) of GTUs can be minimum. By applying the proposed MDE, a ten-TGUs system can reduce the GC effectively compared to the conventional Differential evolution (DE) and other previous algorithms. So, MDE is an effective optimization tool, and it is applied for another more complicated problem with four quarters of years, the ten TGUs and SPGUs. The large and complex problem can reach the most optimal generation solution.

## 1. INTRODUCTION

Economic Load Dispatch (ELD) is a significant problem in optimizing power systems. It primarily focuses on finding the optimal allocation of power generation among various generators to meet the load demand while minimizing costs or achieving other objectives [1-3]. The objective function of ELD is typically to minimize total electricity generation cost (TGC), which involves minimizing the usage of expensive fuels such as natural gas, coal, or oil. Other objective functions can also be considered in ELD besides cost minimization. One such objective is minimizing total toxic emissions, which aims to reduce the environmental impact of power generation. Maximizing total profit can also be an objective, particularly in electricity market scenarios where generators aim to maximize their revenues. By considering multiple fuel option constraints [4-9] and prohibit zones [10] in the ELD problem, the optimization process becomes more realistic and aligned with the operational constraints and regulations of the power system. This ensures that the optimal solution obtained accounts for the availability of different fuel options and complies with the designated prohibit zones, thereby providing a more accurate and feasible dispatch strategy.

Various meta-heuristic algorithms are applied to determine the optimal solution to ELD problems, and their ability is also demonstrated in each application over the classical computing models. Specific algorithms applied to solve ELD can be listed, such as genetic algorithm (GA) [11], grey wolf optimization (GWO) [12], truncate swarm optimizer (TSO) [13], water cycle algorithm (WCA) [14], biogeography optimization (BO) [15], and ameliorated dragonfly algorithm (ADA) [16]. Besides, these algorithms are continuously improved to deal with the higher degree of complexity of ELD problems, which has substantially increased over time. For example, there are countless versions of PSO, such as quantum-behaved PSO (QBPSO) [17], simplex search-based PSO (SSB-PSO) [18], double weight-based PSO (DW-PSO) [19], dynamic particle swarm optimization (DPSO) [20]. Similar to PSO, there are also several improved versions derived from the original GA, such as the non-dominated sorting-based genetic algorithm (NSGA) [21]. DE is also another case; the original version is the foundation for different modified versions, such as a hybrid adaptive Differential Evolution (HADE) based on Gaussian tail mutation [22], efficient and new modified differential evolution algorithm (ENMDE) [23], novel differential evolution [24], or modified differential evolution (MDE) [25]. Besides, the improved version of other meta-heuristic algorithms is also applied to solve the CE-ELD effectively, such as the improved cuckoo search algorithm (ICSA) [26], the modified anti-predatory particle swarm optimization (MAPSO) [27]. In addition to that,

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other complex and large-scale problems in power systems have been solved successfully and effectively by applying meta-heuristic algorithms and their modified version, such as linear and nonlinear coordination of directional overcurrent relays [28], optimal power losses in distribution network [29], optimal reactive power dispatch [30] or optimal rapid changing stations in distribution network [31].

The load demand constantly fluctuates up and down according to the hours of the seasons of the year. The hourly, quarterly, and yearly load demand charts are collected and presented [32]. This is also a matter of concern when solving ELD problems. Moreover, at present, the potential of renewable energy is huge, especially solar energy. Many studies have focused on the ELD problem associated with solar energy [33,34]. Global Solar is a website that provides detailed data on actual solar potential worldwide [35].

This study focuses on solving multi-fuel ELD problems with different load levels. From there, develop a set of optimal solutions for all loads to meet the problem in real-time with continuously changing loads and the capacity of solar energy.

The fundamental contributions of this research are briefly summarized as follows:

- Prove that MDE is more efficient than DE in solving the ELD problem with multiple fuel option constraints.
- Find the optimal solution set for different load demands to meet the needs of solving the problem in real-time when the load changes hourly, seasonally, and annually.

## 2. PROBLEM FORMULATION

### *2.1. Objective*

As mentioned earlier, this paper focuses on minimizing the TGC of all thermal units (TGUs) existing in the power system as the main objective function. The mathematical expression of the objective function is given below [7]:

$$Minimize\ TGC = \sum_{t=1}^{N_{TG}} GC_t \tag{1}$$

with,

$$GC_t = a_t + b_t PG_t + c_t PG_t^2 \quad with\ t = 1, \dots, N_{TG} \tag{2}$$

where, $GC_t$ is the generation cost of the TGU $t$; $a_t$, $b_t$, and $c_t$ are the fuel utilization coefficient of the TGU $t$; $PG_t$ is the active power produced by the TGU $t$; and $N_{TG}$ is the number of TGU existing in the given power plant.

While multiple fuel constraints of TGU is evaluated, Equation (2) is revised by the following expressions below [8]:

$$GC_t = \begin{cases} a_{t,1} + b_{t,1}PG_t + c_{t,1}PG_t^2; if\ PG_t^{min} \le PG_t \le PG_t^1 \\ a_{t,2} + b_{t,2}PG_t + c_{t,2}PG_t^2; if\ PG_t^1 \le PG_t \le PG_t^2 \\ \dots \\ a_{t,n} + b_{t,n}PG_t + c_{t,n}PG_t^2; if\ PG_t^{n-1} \le PG_t \le PG_t^{max} \end{cases} \tag{3}$$

where, $a_{t,n}, b_{t,n}, c_{t,n}$ are the cost coefficients of TGU $t$ for the $nth$ power level; $PG_t^{min}$ and $PG_t^{max}$ are the lowest and highest of active power produce by TGU $t$.

### *2.2 The involved constraints*

This constraint in solving the ELD problem is mainly about the same power between the supplying side and the demanding side. It means that the total power produced by all generating sources on the supplying side must equal the amount of power requested by the demanding side. The mathematical model of this is presented in the following equation [33]:

$$\sum_{t=1}^{N_{TG}} PG_t + PS - PD - PL = 0 \tag{4}$$

where, $PS$ are the active power supplied by SPGUs; $PD$ is the power demanded; $PL$ is the power loss in the transmission process from supplying side to the demanding side; and $PL$ is quantified by using the following mathematical model [27]:

$$PL = \sum_{t=1}^{N_{TG}} \sum_{k=1,k\neq t}^{N_{TG}} PG_t Y_{tk} PG_k + \sum_{t=1}^{N_{TG}} Y_{0t} PG_t + Y_{00} \tag{5}$$

where, $Y_{tk}$, $Y_{0t}$, and $Y_{00}$ are the loss coefficients.

**The limits of TGUs:** The power produced must follow economic and physical limits as below [9]:

$$PG_t^{min} \le PG_t \le PG_t^{max} \tag{6}$$

### *2.3. The power generation models of renewable energy sources*

The Global Solar Atlas (GSA) is an online platform developed by the World Bank Group and the International Renewable Energy Agency (IRENA). It provides access to solar resources and photovoltaic potential data for locations worldwide. The GSA aims to support policymakers, researchers, investors, and individuals in assessing and planning solar energy projects. The GSA offers various features and data sets, including Solar Resource Assessment, SPGUs Potential Assessment, SPGUs Performance, Maps and Charts, and Data Download. One SPGU with a capacity of 450MW is located at the coordinates 11.700359° and 109.027369°. By using Global Solar Atlas [35], the power output data of this plant can present in Figure 1 and 2:

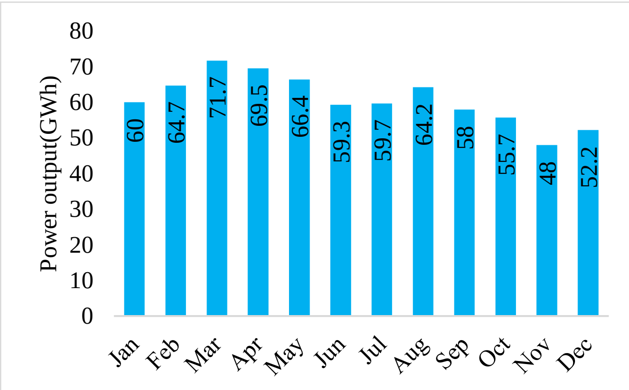



**Fig. 1. The monthly power output supplied.**

| | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 - 1 | | | | | | | | | | | | |
| 1 - 2 | | | | | | | | | | | | |
| 2 - 3 | | | | | | | | | | | | |
| 3 - 4 | | | | | | | | | | | | |
| 4 - 5 | | | | | | | | | | | | |
| 5 - 6 | | | | 2 | 3 | 3 | 2 | 2 | 2 | 2 | 0 | |
| 6 - 7 | 15 | 18 | 28 | 46 | 51 | 44 | 38 | 40 | 43 | 45 | 34 | 22 |
| 7 - 8 | 83 | 98 | 113 | 128 | 128 | 113 | 105 | 113 | 119 | 115 | 100 | 87 |
| 8 - 9 | 157 | 182 | 192 | 206 | 196 | 181 | 171 | 187 | 190 | 178 | 157 | 150 |
| 9 - 10 | 216 | 246 | 250 | 260 | 246 | 231 | 222 | 240 | 238 | 225 | 195 | 200 |
| 10 - 11 | 254 | 294 | 292 | 295 | 277 | 259 | 254 | 271 | 262 | 246 | 221 | 231 |
| 11 - 12 | 273 | 319 | 313 | 311 | 289 | 269 | 263 | 279 | 265 | 247 | 228 | 244 |
| 12 - 13 | 277 | 321 | 314 | 309 | 283 | 260 | 254 | 274 | 254 | 242 | 219 | 239 |
| 13 - 14 | 252 | 298 | 291 | 283 | 256 | 230 | 229 | 247 | 220 | 209 | 187 | 209 |
| 14 - 15 | 205 | 251 | 245 | 232 | 199 | 183 | 182 | 200 | 170 | 156 | 144 | 164 |
| 15 - 16 | 137 | 179 | 172 | 157 | 136 | 126 | 123 | 134 | 113 | 95 | 88 | 101 |
| 16 - 17 | 63 | 92 | 87 | 76 | 66 | 63 | 64 | 68 | 52 | 36 | 28 | 37 |
| 17 - 18 | 5 | 14 | 16 | 13 | 13 | 14 | 16 | 15 | 5 | 2 | | 1 |
| 18 - 19 | | | | | | | | | | | | |
| 19 - 20 | | | | | | | | | | | | |
| 20 - 21 | | | | | | | | | | | | |
| 21 - 22 | | | | | | | | | | | | |
| 22 - 23 | | | | | | | | | | | | |
| 23 - 24 | | | | | | | | | | | | |
| Sum | 1,935 | 2,310 | 2,313 | 2,317 | 2,143 | 1,976 | 1,925 | 2,070 | 1,933 | 1,797 | 1,601 | 1,684 |

**Fig. 2. Total photovoltaic power output [MWh].**

## 3. THE APPLIED METHOD

### *3.1 The original version of Differential evolution algorithm*

The algorithm is structured by the same framework as the others in the class. That means the optimal process must go through several steps, including the Initialization, the update process, the selection, etc., before reaching an optimal solution [24]. For a better understanding, the main steps of the whole optimization process are presented in the following subsections:

***The initialization***

As mentioned earlier, the optimal process of DE must first complete the initialization step. A particular population is randomly generated using the mathematical model below in this step [24]:

$$D_s^j = D_s^{j,min} + RN \times (D_s^{j,max} - D_s^{j,min}) \quad (7)$$

where, $D_s^j$ is the $s^{th}$ solution of the population with $s$ = 1, 2, …, *Po* and *Po* is the population size; *j* is the $j^{th}$ variable of the $s^{th}$ solution; $D_s^{j,min}$ and $D_s^{j,max}$ are the lowest and highest boundaries of the $j^{th}$ variable of $s^{th}$ solution; $RN$ is the random value between zero and one.

***The update process***

The update process will take place after the initialization is completed. DE fulfills its update process through two subprocesses, including the mutation process and the crossover process [24]. The computing models of these subprocesses are presented below:

- ***The mutation subprocess***

In this phase, all the solutions are newly updated using the three random solutions and the mutation coefficient. Specifically, the first solution on the set of three is used to execute the neighboring exploration, while the other two create distant differences from the first one. To be more specific, this process is formulated by the expression below [24]:

$$A_s^{new} = D_{rnd1} + mc(D_{rnd2} - D_{rnd3}) \quad (8)$$

where, $A_s^{new}$ is the $s^{th}$ new solution update in this phase; $D_{rnd1}$, $D_{rnd2}$, and $D_{rnd3}$ are the three random solution selected from the initial population; $mc$ is the mutation coefficient.

- ***The crossover subprocess***

The crossover process is employed to diversify the solutions in the initial population. The diversifying action is executed by using the expression below [24]:

$$B_s = \begin{cases} A_s^{new} & \text{if} \quad RN_s \le CR \\ D_s, & \text{otherwise} \end{cases} \quad (9)$$

where, $B_s$ is the newly update solution in the crossover subprocess $RN_s$ is the random value between zero and one; $CR$ is the crossover coefficient.

***The selection procedure***

This procedure is performed to retain the high-quality solutions for the next iteration and abandon the low-quality ones. The quality degree of a solution is determined based on its fitness value. That means that a solution with better fitness value is unarguably acknowledged as a higher-quality solution. The mathematical expression of the selection procedure is presented as follows [24]:

$$D_s = \begin{cases} D_s & \text{if} \quad Fit_{D_s} \le \quad Fit_{B_s} \\ B_s, & \text{otherwise} \end{cases} \quad (10)$$

where, $Fit_{D_s}$ and $Fit_{B_s}$ are, respectively, the fitness value of the current solution and the newly updated solution.

### *3.2 The modified version of Differential evolution algorithm (MDE)*

The modified version of Differential evolution algorithm

(MDE) is proposed based on the modifications in the mutation subprocess to reach the high quality of the newly updated solutions. The following expressions give the modifications:

$$\text{sec1 } A_s^{new} = D_{rnd1} + mc(D_{rnd2} - D_{rnd3}) \quad (11)$$

$$\text{sec2 } A_s^{new} = D_{rnd1} + mc(D_{rnd2} - D_{rnd3} + D_{rnd4} - D_{rnd5}) \quad (12)$$

$$\text{top1 } A_s^{new} = D_{Best} + mc(D_{rnd1} - D_{rnd2}) \quad (13)$$

$$top\ 2\ A_s^{new} = D_{Best} + mc(D_{rnd1} - D_{rnd2} + D_{rnd3} - D_{rnd4}) \quad (14)$$

$$present - to - top\ A_s^{new} = D_s + mc\,(D_{Best} - D_s + D_{rnd1} - D_{rnd2}) \quad (15)$$

Equations (11) – (15), $D_{rnd4}$ and $D_{rnd5}$ are the fourth and the fifth random solutions selected from the initial population; and $D_{Best}$ is the best solution at the present consideration. Note that, the given modifications are divided into three groups, Group 1 with Equations (11) – (12), Group 2 with Equations (13) – (14), and Group 3 with Equation (15). If the current solution *s* has worse fitness than the mean solution, Group 2 is selected. On the contrary, either Group 1 or Group 3 is used. If Group 1 is used, either Equation (11) or Equation (12) is used.

## 4. RESULTS AND DISCUSSION

This section applies the DE and MDE to solve ELD problems with multiple fuel option constraints and different load demand levels. The primary objective function of the problems considered is to minimize the TGC. The methods are examined with 50 independent runs, and the initial control parameters, including the population size (*Po*) and the highest number of iterations ($HM_{max}$), are equally set at 50 and 100, respectively.

The whole research is conducted on a personal computer with a 2.7 GHz central processing unit (CPU) and 8GB of random access memory. The related coding and simulation are executed using MATLAB version 2018b.

### *4.1. Case 1*

The results obtained from 50 runs of the two methods with load demand cases 2400, 2500, 2600, and 2700 (MW) are shown in Figure 3. The results in Figure 3 show that MDE always obtains better TGCs than DE in all four load cases. The minimum cost (Min.cost), the average cost (Aver.cost), and the minimum cost (Max.cost) of 50 runs in The results in Table 1 indicate that the MDE can effectively find a more optimal solution. Specifically, when the load demand is set to 2400 (MW), MDE obtained $481,723, 0.091% lower than DE. When the load demand is set to 2500 (MW), MDE obtained $526.239, 0.071% lower than DE. Similarly, for a load demand of 2600 (MW), MDE obtained $574.381, which is 0.058% lower than DE.

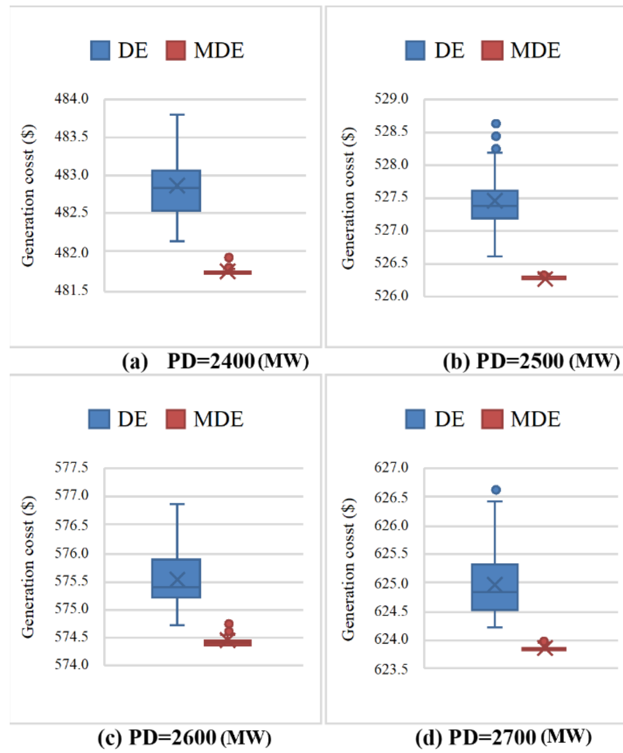



**Fig. 3. Results obtained by DE and MDE.**

**Table 1. The comparison between DE and MDE while solving the ELD with different load demand values**

| Load (MW) | Method | Min. cost($) | Aver. cost($) | Max. cost($) | STD |
|---|---|---|---|---|---|
| 2400 | DE | 482.162 | 482.876 | 483.809 | 0.422 |
| | MDE | 481.723 | 481.747 | 481.929 | 0.037 |
| 2500 | DE | 526.613 | 527.455 | 528.681 | 0.469 |
| | MDE | 526.239 | 526.268 | 526.387 | 0.031 |
| 2600 | DE | 574.717 | 575.541 | 576.895 | 0.482 |
| | MDE | 574.381 | 574.454 | 574.768 | 0.112 |
| 2700 | DE | 624.212 | 624.967 | 626.644 | 0.550 |
| | MDE | 623.810 | 623.855 | 623.990 | 0.040 |

Finally, when the load demand is set to 2700 (MW), MDE obtained $623.810, 0.064% lower than DE. Table 2 compares the best results obtained by MDE with previous studies and demonstrates that MDE consistently achieves electricity TGCs comparable to or better than those reported in the literature. When the load demand is set to 2400 (MW), MDE obtained $481,723, which is the same value as ALHN [4], MPSO [5], ARDGA [7], and ACSA [9], and approaches. Furthermore, MDE outperforms the SDE [6] and IEP [8] approaches. Similarly, when the load demand is set to 2500 (MW), MDE obtained $526,239, which is the same value as the ALHN [4], MPSO [5], and ACSA [9] approaches. Moreover, MDE outperforms the SDE [6], ARDGA [7], and IEP [8] approaches by 0.016%, 0.004%, and 0.012%, respectively. For the load demands of 2600 and 2700 (MW), MDE obtained $574,381 and $623,809, respectively, which is the same value as the ALHN [4], MPSO [5], and ACSA [9] approaches.

**Table 2. The comparison cost ($) between MDE and other methods while solving ELD with different load demand values**

| Methods | 2400 (MW) | 2500 (MW) | 2600 (MW) | 2700 (MW) |
|---|---|---|---|---|
| ALHN [4] | 481.723 | 526.239 | 574.381 | 623.809 |
| MPSO [5] | 481.723 | 526.239 | 574.381 | 623.809 |
| SDE [6] | 481.863 | 526.323 | 574.538 | 623.923 |
| ARDGA [7] | 481.723 | 526.259 | 574.405 | 623.828 |
| IEP [8] | 481.779 | 526.304 | 574.473 | 623.851 |
| ACSA [9] | 481.723 | 529.239 | 574.381 | 623.809 |
| MDE | 481.723 | 526.239 | 574.381 | 623.809 |

### *4.2. Case 2*

The load capacity continuously varies by hour, day, and year. According to the data from [32], we have the load graph of 4 quarters, as shown in Figure 4. The figure shows that the load demand for quarter one is the lowest while that of quarter 3 is the largest. Solar energy also changes hourly and seasonally [35]. The average power output for each hour of each month is shown in Fig 2. In this case, this paper used MDE to determine the optimal solution for each load level.

The optimal TGC for each load level is shown in Figure 5. The optimal power output of each TGU is shown in Figure 6. The figure shows that each selected unit's capacity varies depending on the load demand. From the data in Figure 6, we can solve for all cases of the load chart. Specifically, here we have four load graphs for four quarters combined with the output capacity of solar energy in the first month of each quarter shown in Figure 7a, 8a, 9a, and 10a. From the data in Figure 6, we can solve for all cases of the load chart. The solutions for each quarter are shown in Figure 7b, 8b, 9b, and 10b, respectively.

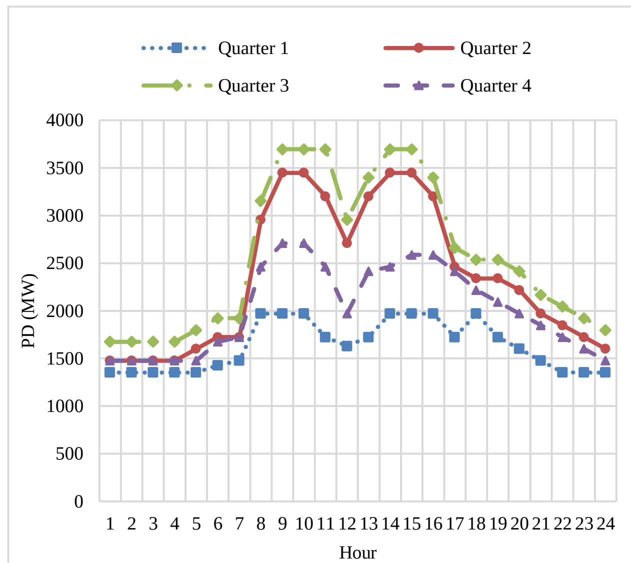



**Fig. 4. The average load demand chart of four quarter.**

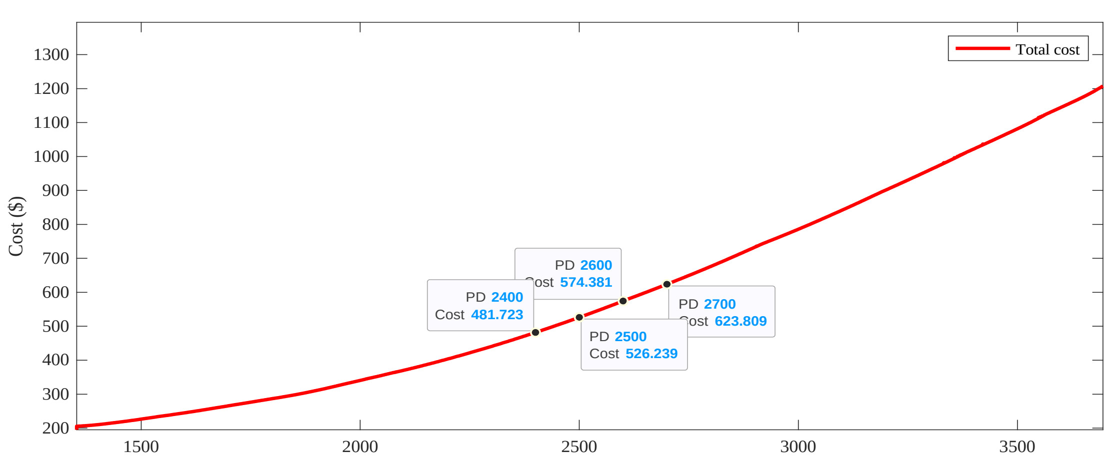



**Fig. 5. Optimal TGCs chart corresponding to each load demand level**

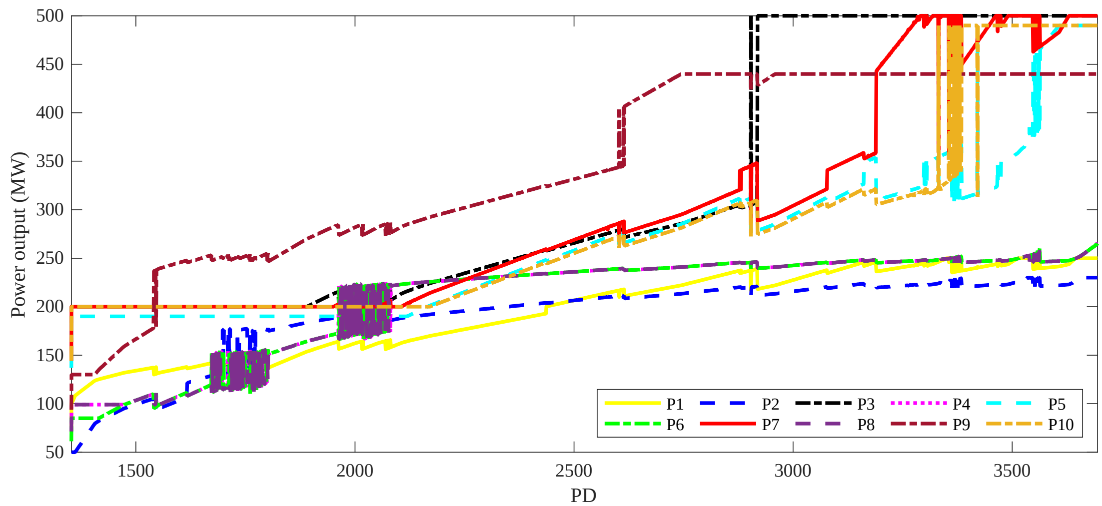
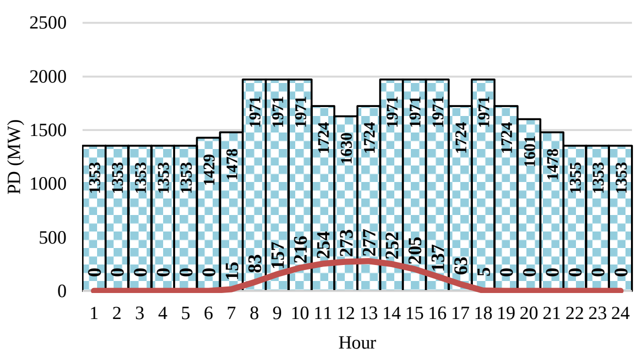
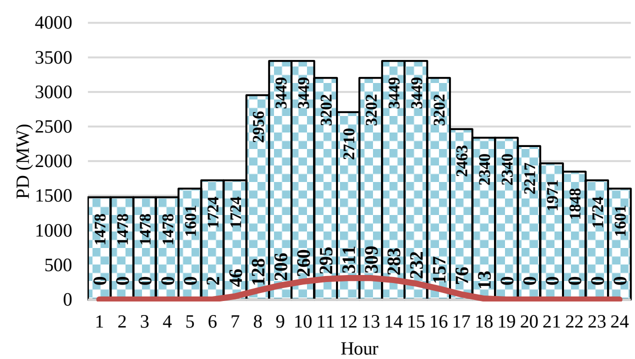


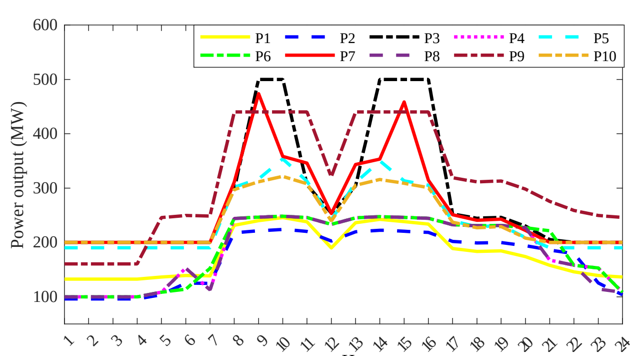

**Fig. 6. Optimal solutions corresponding to each load demand level.**




**(a) Load demand of Quarter 1 and the power output of SPGUs in January**

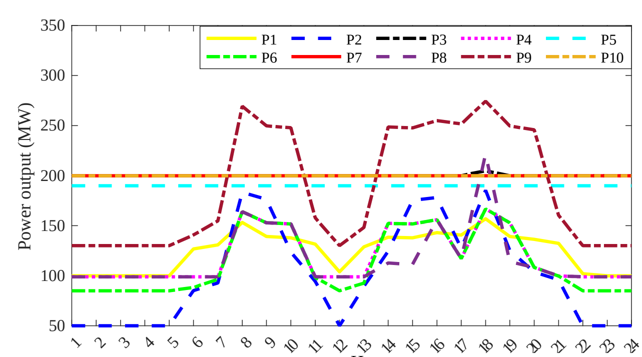



**(a) Load demand of Quarter 2 and the power output of SPGUs in April**



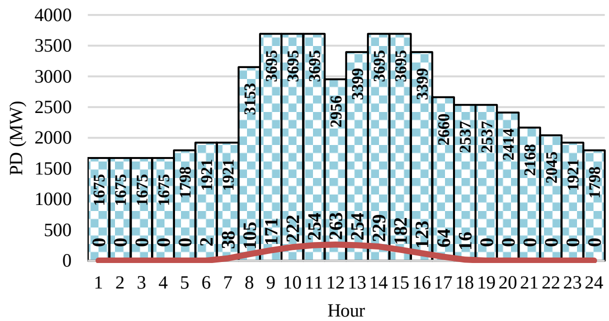

**(b) Solution**

**Fig. 7. Load demand chart and solution of Quarter 1**

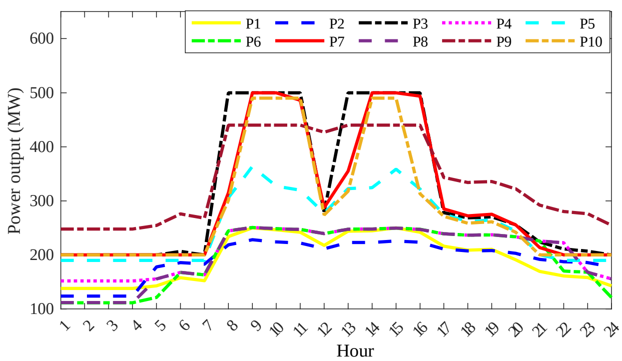



**(b) Solution**

**Fig. 8. Load demand chart and solution of Quarter 2**

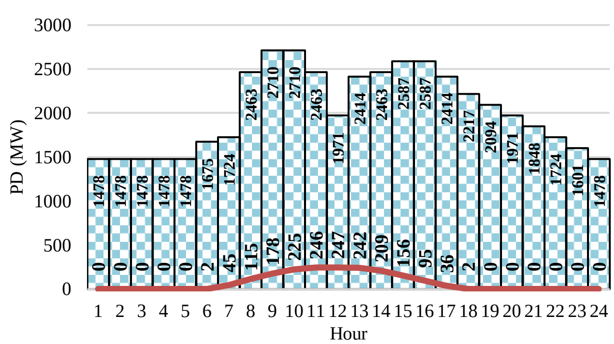



**(a) Load demand of Quarter 3 and the power output of SPGUs in July.**

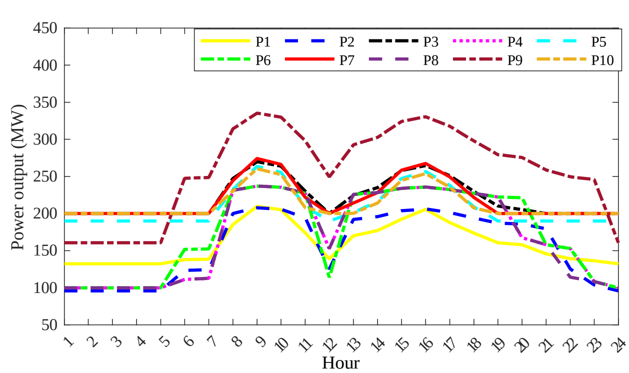



**(b) Solution**

**Fig. 9. Load demand chart and solution of Quarter 3.**




**(a) Load demand of Quarter 4 and the power output of SPGUs in October.**




**(b) Solution**

**Fig. 10. Load demand chart and solution of Quarter 4.**

## CONCLUSIONS

In conclusion, this study has demonstrated the effectiveness of the modified differential evolution algorithm in solving the economic load dispatch problem with multiple fuel option constraints. The study highlights the potential of the MDE as a reliable and efficient algorithm to solve complex optimization problems. This paper finds all solutions for each load demand level that make data and solve the problem with different load demands and renewable energy. Future studies can build on this research by exploring enhancements and extensions to the MDE algorithm and ways to find solutions to address additional real-time challenges in power system optimization.

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