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Research Article

Electricity Generation Cost Optimization Based on Lagrange Function and Local Search

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Abstract: This paper proposes a method based on the Lagrange optimization function and local search technique for minimizing the total cost of two power systems. The first system comprises ten multiple fuel thermal units (MFTUs) while the second system combines the first system with renewable energies, solar and wind power. The proposed method has advantages over its conventional method without a local search technique, called the conventional Lagrange function-based method (CLM), such as having the same parameters and exploiting other search spaces after getting convergence. The proposed method is more effective than CLM for the first system with the last case of load demand. In addition, the proposed method has better costs than previous algorithms, such as the Hierarchical numerical method (HNUM), Hopfield neural network, Adaptive Hopfield neural networks (AHNN) and modified Lagrange neural network (MLANN). Especially, the proposed method can find smaller costs than them, up to \$6.78, corresponding to 1.4% for Case 1, and up to \$2.43, corresponding to 0.4% for Case 4. Only the proposed method is tested on the second test system. The simulation results indicate that the method is very efficient for the problem with solar and wind energies and multiple fuel thermal units.

Keywords: Renewable energies; Optimal generation dispatch; Lagrange function; Multiple fuels; Wind power; Solar power.

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1. Introduction

Economic load dispatch (ECLD) is one of the most significant power system optimization operation problems that has attracted a high number of researchers [1]. The ECLD issue has been solved by multiple methods so far. The ECLD can be defined as finding the least power generation costs for generating units or power plants to satisfy the demand at a given hour. At the same time, it satisfies the system constraints of the generation limits and system load demand. Traditionally, in ECLD, the cost functions of these units or plants have been approximately represented by a single second-order function. For each fuel, one function is employed and the task of the problem is to select the most suitable fuel and power for each plant.

The lambda-iteration technique, based on points, participation factors, and gradient methods, has been utilized to solve the ECLD problem with the single quadratic function. The character of cost curves did not restrict the dynamic programming approach (DYP). It can generate global solutions even for plants with prohibited power zones [2]. However, DYP had the weakness of using many trial power values, especially for systems with a high number of plants. The Differential Evolution algorithm (DE) [3] was proved to be fast in converging to global optimal solutions. The simulated annealing algorithm (SA) [4] was applied to many power systems. However, SA has a large range of values for setting control parameters, and its response is slow for satisfying all complicated constraints.

In the modified Lagrange neural network (MLANN) [5], the dynamic process of Lagrange multipliers was suggested to improve for reaching effective candidate solutions and a quick convergence. However, MLANN has involved a high iteration number in search process, and it coped with oscillations between iterations. A modified Particle swarm optimization algorithm (MPSO) [6] has been proposed for the power systems with optional fuels. Although this method can develop high-quality resolutions within a low estimation time and steady convergence than others, it is sensitive to tuning some weights or other parameters. Self-modified Differential Evolution (SMDE) [7] was an excellent approach to solving the ECLD issue with many effects of valve loading points. The reduced generation schedule cost and minimal simulation time were reached by using Modified Augmented Lagrange Hopfield Network (MALHN) [8].

The differential evolution (DE) was run for ECLD problem with five different configurations of systems [9]. A human behaviors-based search algorithm was applied to minimize cost and emission [10]. An enhanced arithmetic optimization (EAO) was suggested to overcome the shortcomings of the conventional algorithm for a multi-objective problem with data mining technology [11]. A proposed algorithm was applied to choose the most suitable test data of the multi-objective problem [12]. Grey Wolf algorithm was applied to deal with none-convex ECLD optimization problems [13]. Harris Hawk algorithm was run to find optimal solution for many economic load dispatch systems [14]. A supply and demand-based algorithm was run to solve the ECLD and it reached the local and global searches [15]. Hybrid grey wolf algorithm based on a strong learning mechanism has been proposed for the problem [16]. The foraging optimization algorithm, which was developed based on the Spiral Foraging technique, was applied to solve the ECLD problem. Different methods were applied to improve global search and speed up convergence [17]. Approximately all metaheuristic algorithms were more effective than Lagrange functions-based methods shown in [5] and [8], and other earlier methods such as hierarchical numerical method (HNUM) [18], Hopfield neural network (HNN) [19]and Adaptive Hopfield neural networks (AHNN) [20].

These studies mentioned above have successfully solved the ECLD problem with acceptable electricity generation cost; however, the application of renewable energies has not been concerned with reducing the expensive price of fossil fuels such as gas and coal. In recent decades, wind and solar power have been considered in the ECLD problem. A multi-objective problem was established for dealing with two systems with wind turbines and distributed generators [21]. Jaya Algorithm has been implemented for two systems with wind and solar power, considering the uncertainty of wind speed and solar radiation [22]. The study indicated that thermal power plants could reduce generation and cost-effectively with the power. The jellyfish search algorithm was applied to maximize the profit of two power systems with 30 and 118 buses, considering the electricity market and wind power (WTs) [23]. The study indicated that the profit could be great if the wind plants were optimally placed on suitable buses. The ECLD problem is considered a complex system with wind, thermal, solar and hydropower plants [24]. The certain and uncertain wind and solar data were considered in generation cost to minimize the total electricity generation cost of the system. The study indicated that the total cost was mainly influenced by inflows from hydropower plants and the uncertainty of wind and solar.

In this paper, a practical technique founded on the Lagrange multiplier is proposed in order to solve the ECLD issue. The technique's strong point is to develop the problem easily. An initial line of Hybrid incremental cost is selected. In order to display the significance of the suggested technique, it has experimented on two power systems for comaprison with previous algorithms and the conventional Lagrange function-based method (CLM) [25]. The first one is comprised of ten thermal power plants supplying four load values. The second system consider the first one and renewable energy, including one solar power plant and one wind power plants. The results are compared to other approaches. The novelty and contributions of the paper are as follows:

1) Propose a new algorithm based on the Lagrange function. The algorithm can reach better optimal solutions than other Lagrange methods thanks to searching around the best solutions.
2) Consider renewable energies for the thermal power plants using multiple fossil fuels.
3) Reach the smallest generation cost for power systems.

In addition to this section, the paper has other sections as follows: Section 2 presents the problem formulation. Section 3 presents the proposed method based on the Lagrange function and local search. Section 4 shows numerical results. Section 5 summarizes the results and conclusions.

2. Problem formulation

2.1. Wind and solar power generation

Wind generation is calculated depending on wind speed, air density and area of blades. In addition, the generation can be obtained by using characteristics of winds, shown in Equation (1) and plotted in Figure 1.

$$P_{wind} = \begin{cases} 0, & (V_w < V_w^{min}\ ;\ V_w > V_w^{max}) \\ P_w^{Rate} \times \dfrac{(V_w - V_w^{min})}{(V_w^{Rate} - V_w^{min})}, & V_w \in [V_w^{min}, V_w^{max}] \\ V_w^{Rate} & V_w \in [V_w^{Rate}, V_w^{max}] \end{cases} \tag{1}$$

Where $W_w^{min}, V_w^{max}, V_w^{Rate}$ are the minimum, maximum and rated wind speeds; V_w is the real wind speed; and P_w^{Rate} is the rated active power of wind power plant.

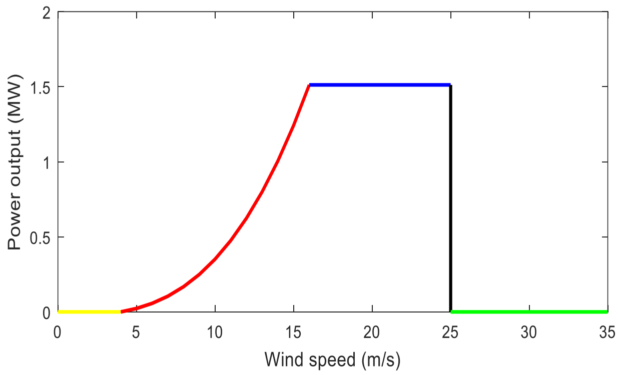

Figure 1. A typical wind turbine characteristic

Similarly, the generation of solar power plants is dependent on the environement and solar radiation as Equation (2).

$$P_{solar} = \begin{cases} \dfrac{(R_s)^2}{(FR_s.SR_s)} \cdot P_{solar}^{Rate}, & (0 < R_h < SR_s) \\ \dfrac{R_h}{FR_s} \cdot P_{solar}^{Rate}, & (R_s \geq SR_s) \end{cases} \tag{2}$$

Where P_{solar}^{Rate} is the rated power of the solar power plant; SR_s is the standard radiation (W/m[2]); and R_s is the real solar radiation.

2.2. Objective function of the ECLD Problem

The Objective function of the ECLD problem is present in Equation (3).

$$\text{Min}Cost_T = \min \sum_{i=1}^{N} F(P_{Ti}) \tag{3}$$

Where $F(P_{Ti})$ is the generation cost of the i^{th} thermal power plant; P_{Ti} is the generation of the ith power plant. The generation cost is obtained by Equation (4).

$$F(P_{Ti}) = \begin{cases} \dfrac{1}{2} a_{i1} P_{Ti1}^2 + b_{i1} P_{Ti1} + c_{i1}\ , if\ P_{Ti1}^{min} \leq P_{Ti1} \leq P_{Ti1}^{max}\ for\ fuel\ 1 \\ \dfrac{1}{2} a_{ik} P_{Tik}^2 + b_{ik} P_{Tik} + c_{ik}\ , if\ P_{ik}^{min} \leq P_{ik} \leq P_{ik}^{max}\ for\ fuel\ k \end{cases} \tag{4}$$

Where P_{Ti1} is the generation of the i^{th} thermal power plant with fuel 1; P_{Tik} is the generation of the i^{th} thermal power plant with the fuel k. k is set to 1 to N_i where N_i is the number of fuels of the ith power plant.

2.3. Constraints

Power balance constraint: For the systems without renewable energies, all thermal power plants supply to load demand (P_D) as shown in Equation (5) below:

$$\sum_{i=1}^{N} P_{ik} - P_D = 0 \tag{5}$$

However, the study also considers the generation from wind and solar power plants. So, the power balance constraint is modified as Equation (6).

$$\sum_{i=1}^{N} P_{Ti} + P_{Wind} + P_{Solar} - P_D = 0 \tag{6}$$

Generation limit constraints: generations from thermal power plants, wind and solar power plants must satisfy each plant's capacity and economic issues. The constraints are as Equations (7)-(9).

$$P_{Ti}^{min} \leq P_{Ti} \leq P_{Ti}^{max} \tag{7}$$

$$P_{Wind}^{min} \leq P_{Wind} \leq P_{Wind}^{max} \tag{8}$$

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

In addition, the load is also constrained to ensure that the possibility that the load cannot be supplied fully never happens. The constraint is as Equation (10).

$$P_D \leq \sum_{i=1}^{N} P_{Ti}^{max} \tag{10}$$

The constraint means that the generation from wind and solar power plants can be zero, and all thermal power plants must work at full capacity for the case.

The Lagrange function is established as Equation (11).

$$L = \sum_{i=1}^{N} F(P_{Ti}) - \lambda \left(\sum_{i=1}^{N} P_{Ti} + P_{Wind} + P_{Solar} - P_D \right) \tag{11}$$

To solve the problem, the function is taken derivatives as Equations (12)-(14).

$$\begin{aligned} \frac{\partial L}{\partial P_{Ti}} &= \frac{\partial C_T(P_{Ti})}{\partial P_{Ti}} - \lambda = 0, \\ \frac{\partial L}{\partial \lambda} &= \sum_{i=1}^{N} P_{Ti} + P_{Wind} + P_{Solar} - P_D = 0 \end{aligned} \tag{12}$$

$$\lambda = a_{ik} P_{Ti} + b_{ik} \tag{13}$$

$$P_{Ti} = \frac{\lambda - b_{ik}}{a_{ik}} \tag{14}$$

3. Implementation of the proposed method for the ECLD

The ECLD problem can be solved by using the iterative algorithm based on the proposed method. The computation steps are expressed as follows:

Step 1 : Set values to λ and $\Delta\lambda$
Step 2 : Set the fuel $k = 1$
Step 3 : Calculate generation for thermal power plants using Eq. (14)
Step 4 : Check and correct the obtained generations
Step 5 : If $\sum_{i=1}^{N} P_{Ti} + P_{Wind} + P_{Solar} < P_D$, set $\lambda = \lambda + \Delta\lambda$ and go back to step 3. Otherwise, Go to step 6.

Step 6: If $\sum_{i=1}^{N} P_{Ti} + P_{Wind} + P_{Solar} > P_D$, set $\lambda = \lambda - \Delta\lambda$ and go back to step 3. Otherwise, go to Step 7.
Step 7 : If $k < N_i$ set $k = k + 1$ and go back to Step 1. Otherwise, accept λ, $\Delta\lambda$ and obtained generations and go to Step 8.
Step 8 : Decrease λ to $(\lambda - \Delta\lambda)$ for a half thermal power plant number, which are randomly picked.
Step 9 : Increase λ to $\lambda + \Delta\lambda$ for remaining half thermal power plant number.
Step 10: Calculate generation cost for each plant and total cost for all plants.
Step 11: If the total cost is smaller cost than optimal cost obtained at Step 7, save the total cost and new generation. Otherwise, go back to Step 8.

4. Numerical results

In this section, the applied method is run on two test systems. The first system comprises ten thermal power plants, and the second system combines the ten existing thermal power plants in the first system [5] and two renewable power plants, one wind power plant and one solar power plant. The task of the algorithm is to find the most effective generation of the thermal power plants for four study cases with loads from 2,400 MW to 2,700 MW. The simulation case for the two systems are as follows:
Case 1: Load of 2,400 MW
Case 2: Load of 2,500 MW
Case 3: Load of 2,600 MW
Case 4: Load of 2,700 MW

It is supposed that the wind power plant has ten 1.5-MW wind turbines, and the solar power plants have 100,000 solar panels with 300 W for each. So, as the rated wind speed and rated solar radiation, the wind and solar power plants can produce 15 MW and 30 MW. The study considers three hours as follows:

1) The first hour: the wind speed and solar radiation are equal to rated values.
2) The second hour: the wind speed is rated, but the solar radiation is 80% of the rated solar radiation.
3) The third hour: the wind speed equals 80% of the rated, but the solar radiation equals the rated value.

The applied algorithm has been run on the computation software of MATLAB R2016B on a personal computer with 2.0 GHz and 4 GB of RAM. The results of the proposed approach are compared to those from CLM, HNUM [18], HNN [19], AHNN [20], MPSO [6], MLANN [5] and MALHN [8].

4.1. Result comparison for System 1

The results of the proposed approach are compared to those from others as given in Figure 2, Figure 3, Figure 4 and Figure 5. The four figures present the best cost of all algorithms. The proposed method, AHNN [20], MLANN [5], MPSO [6] and MALHN [8] have the same generation cost for Case 1, Case 3 and Case 4. HNUM [18] and HNN [19] have a smaller generation cost than the proposed method for Case 2; however, the total generation of the methods is smaller than 2500 MW. In addition, the proposed method has the same generation cost as its conventional method, CLM for Case 1, Case 2 and Case 3 but the proposed method reaches less cost than CLM for Case 4. That is \$623.809 for the proposed method and \$626.26 for CLM. The reason is that CLM has found the cost of \$626.26 when the power balance constraint was satisfied exactly. We used the error 10^{-3} for the conventional and proposed methods. So, if the deviation is smaller than the error, CLM is stopped, but the proposed method continues to be run for local search. The proposed method used local search and found a better solution than CLM's results. So, the finding of the proposed method is the local search.

From the results above, it can be indicated that the proposed method is effective for the problem with multiple fossil fuels. Applying the proposed method is simpler and more effective than neural network-based methods because it just owns two easy-setting parameters. Compared to metaheuristic algorithms, the proposed method needs a Lagrange function, while these algorithms need a fitness function and population and iteration number settings. On the other hand, the proposed method has the same result for different runs, while other algorithms must run many times to reach the best solution. So, the proposed method is the most suitable for the considered problem.

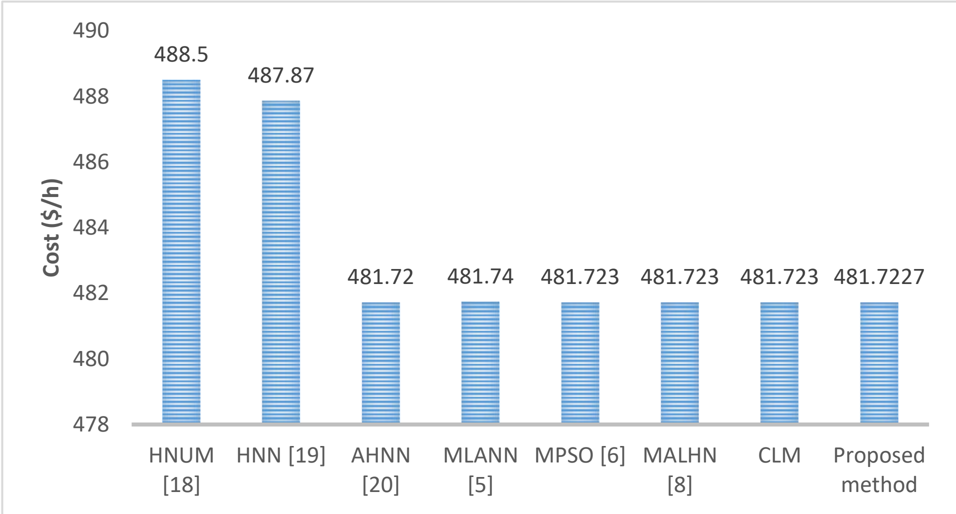

Figure 2. Cost Comparisons for Case 1 of System 1

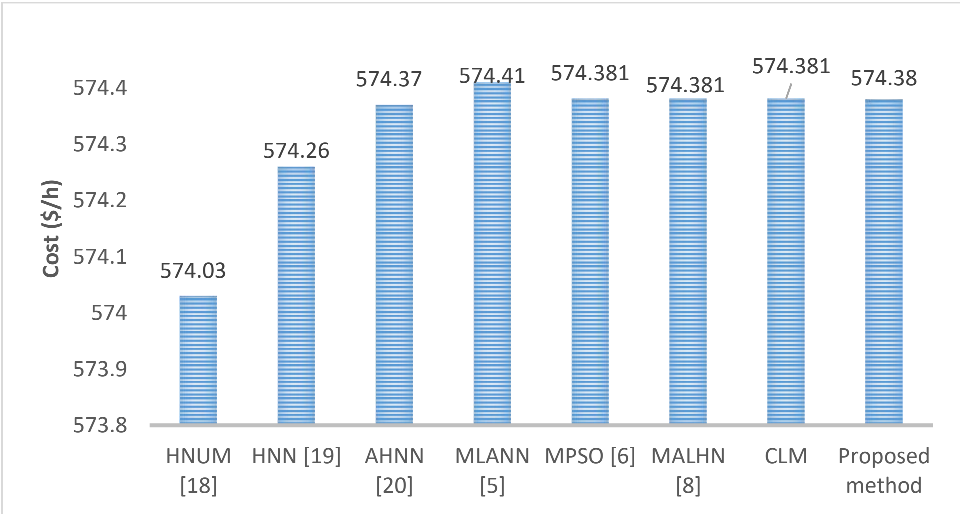

Figure 3. Cost Comparisons for Case 2 of System 1

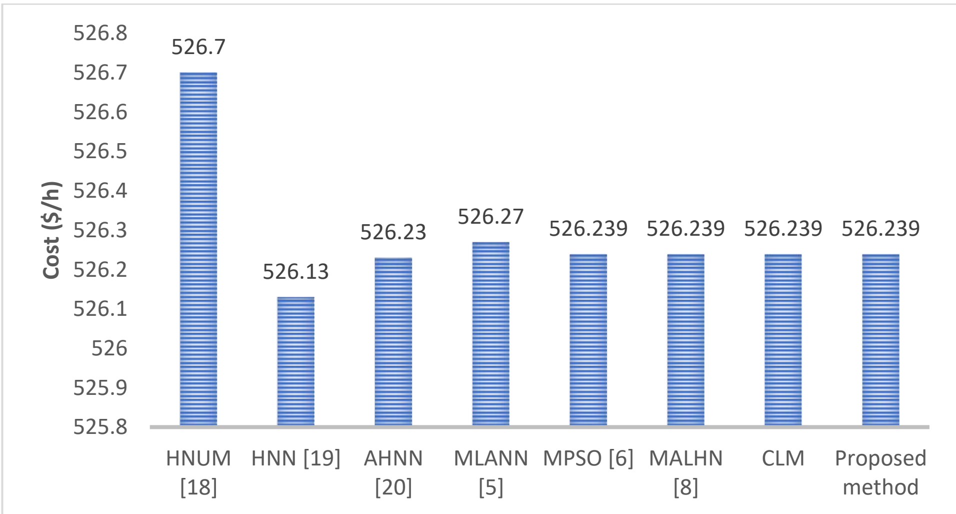

Figure 4. Cost Comparisons for Case 3 of System 1

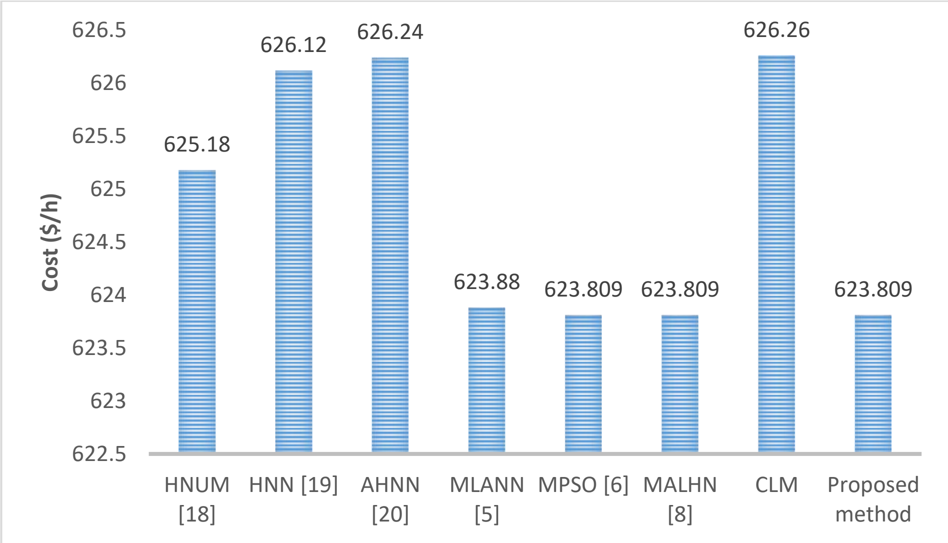

Figure 5. Cost Comparisons for Case 4 of System 1

Clearly, the performance of the proposed method is high for the problem. In fact, the proposed method has reached smaller costs than others, up to $6.78, corresponding to 1.4% for Case 1, and up to $2.43, corresponding to 0.4% for Case 4. So, the generation of thermal power plants found by the proposed method is reliable and highly evaluated. The generation is reported in Figure 6. The generation from different plants is different due to the different fuel cost functions shown in Equation (4) and the study [5]. However, the deviation of generation with the same thermal power plant is not high among the four cases. In fact, the load deviation is only 100 MW due to the load cases of 2400, 2500, 2600 and 2700 MW.

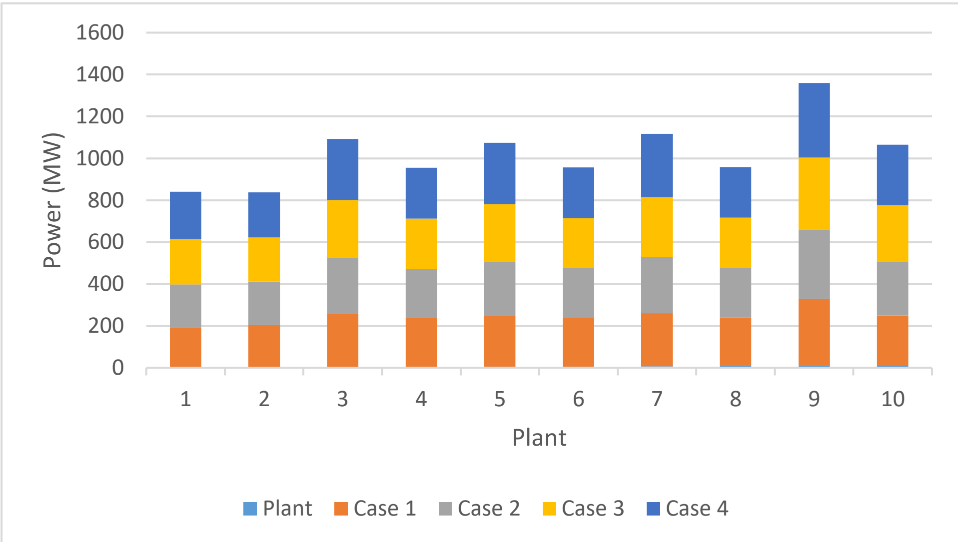

Figure 6. Thermal generation for four study cases of System 1

4.2. The result comparison for System 2

In this Section, only the proposed method is run for system 2 with four load cases. The results are given in Figure 7 for comparing the four cases of System 1 and the four cases of System 2 within three hours. The results indicate that System 2 performs better than System 1, thanks to generating wind and solar power plants. System 2 with hour 1 is the best because its generation costs for four cases are the smallest. System 2 with hour 2 is worse than System 2 with hour 3. Clearly, the solar power plant with a greater capacity than the wind power plant has more impact on the cost.

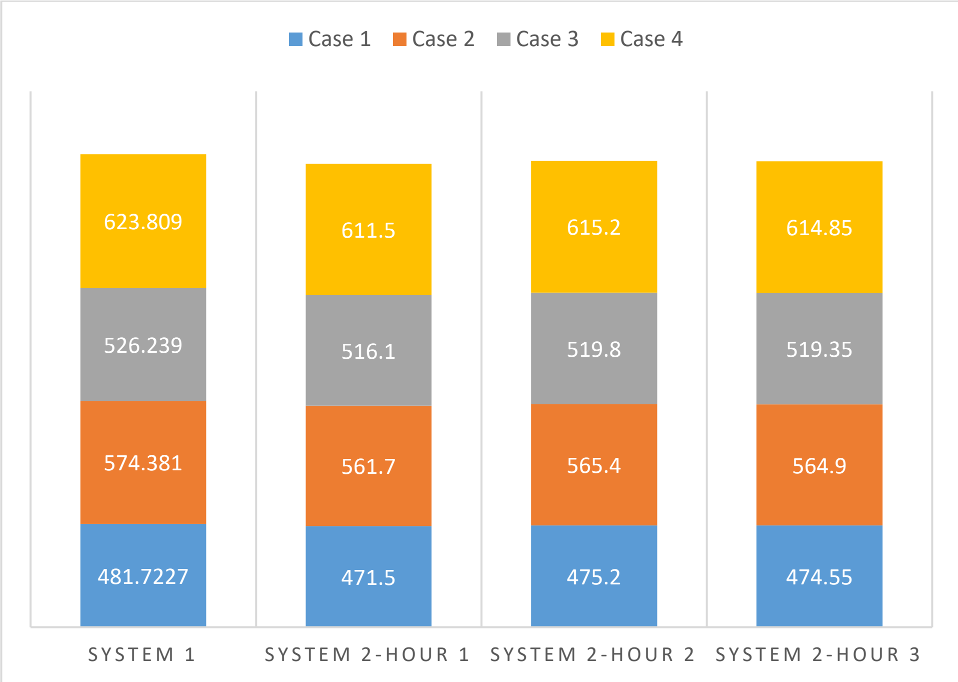

Figure 7. Total cost ($/h) of systems with four study cases.

The generations of thermal, wind and solar power plants in System 2 for the four study cases at hour 1, hour 2 and hour 3 are reported in Figures 8, 9 and 10. The figures indicate that thermal power plants still account for a high generation rate in supplying full demand to loads. If we can increase the capacity of the renewable power plants, the costs from the conventional thermal power plants can be reduced more significantly. The study has not considered the uncertainty of the renewable power plants and used all generated power from the plants. So, the difference in thermal generation among the study cases is small due to the different load demands of 2400, 2500, 2600 and 2700 MW. If the demand increases more significantly, the change will be seen clearer. In the future work of the study, high load demands such as 10,000 or 20,000 MW will be applied for the system in addition to considering the uncertainty of wind and solar.

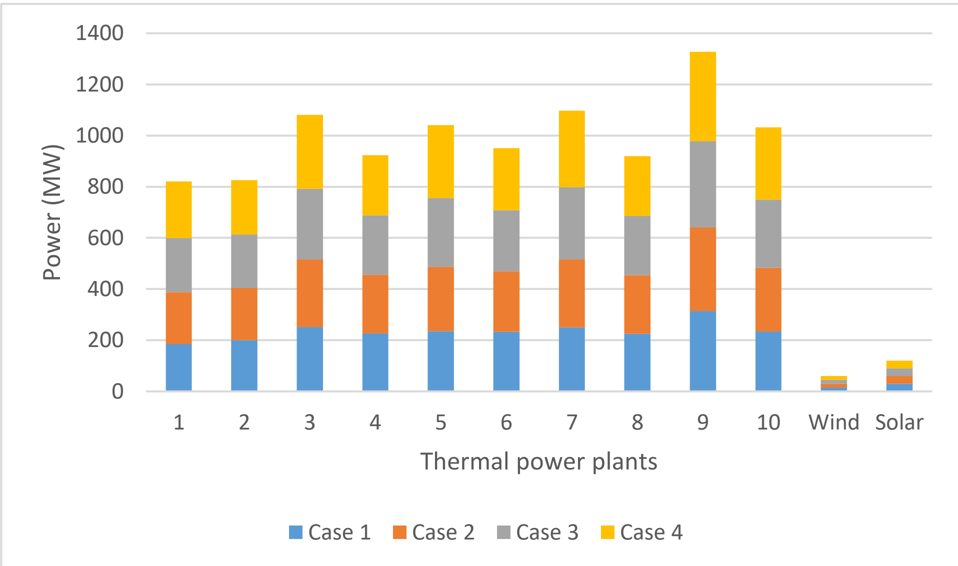

Figure 8. Thermal, wind and solar generations for four study cases at the first hour

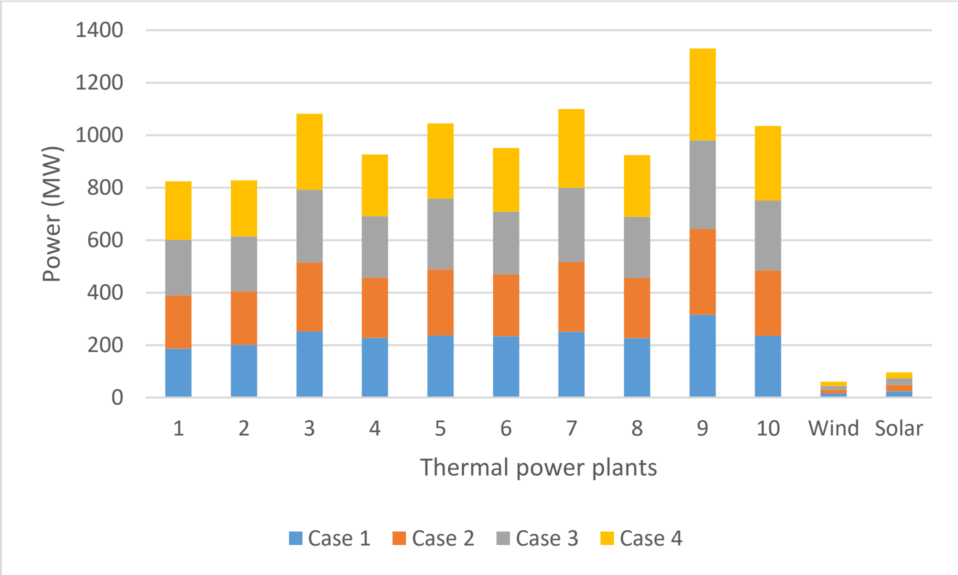

Figure 9. Thermal, wind and solar generations for four study cases at the second hour

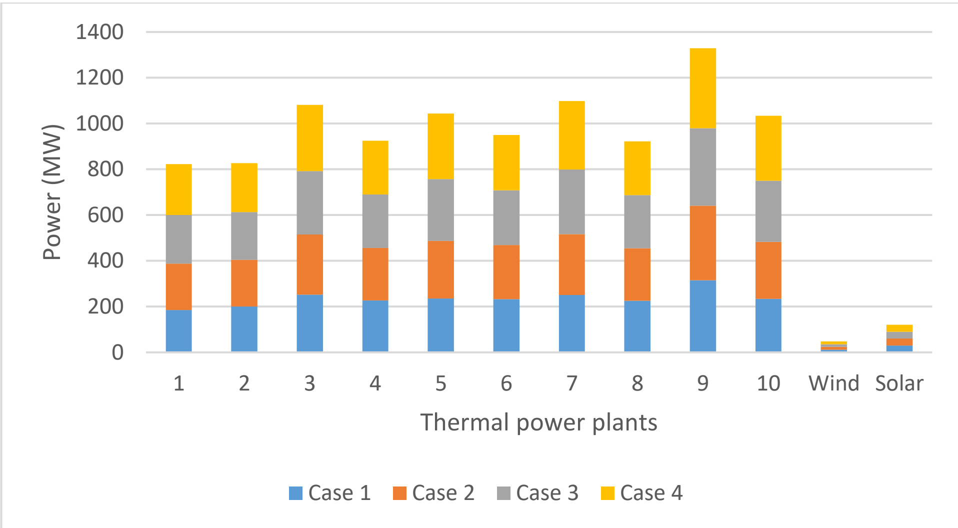

Figure 10. Thermal, wind and solar generations for four study cases at the third hour

5. Conclusions

This paper proposes an effective iterative algorithm based on the Lagrange method to find optimal generations for thermal power plants using multiple fuel options. Two systems were applied in which System 2 was comprised of System 1 and two more renewable power plants, wind and solar power plants. Four load cases of 2,400, 2,500, 2,600 and 2,700 MW were considered to be supplied. The results can be summarized as follows:

- The proposed method could reach equal or the same generation costs compared to other artificial intelligence or metaheuristic algorithm for Case 1, Case 3 and Case 4 of System 1. For Case 2, two other algorithms violated the total generation constraint, so they were still worse than the proposed method even though they found smaller generation cost.
- The proposed method could reach a better solution than its conventional method for Case 4. The conventional method has fallen into local zones and could not find the global optimum solution. However, the proposed method could exploit search spaces effectively using local search techniques.
- System 2 with renewable energies could reach smaller costs than System 1 for four cases.
- System 2, with full generation from wind and solar power plants, reached the smallest cost.

- The generation of wind and solar power plants was much smaller than that of thermal power plants in System 2.

The results indicated that the paper had significant contributions. However, the paper still has shortcomings, such as neglecting power loss on lines and voltage profile of loads, ignoring the total costs of renewable energies. So, the future work of the paper will consider the constraints to have more contributions to power systems.

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Data Availability Statement: Data of the two systems were taken from [5].

Conflicts of Interest: The authors declare no conflict of interest.

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