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Finding Optimal Solutions for an Economic Load Dispatch Problem Considering Thermal, Solar and Wind Power Plants by Using Salp Swarm and Northern Goshawk Optimization Algorithms

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Abstract

This paper proposes a new variant of the traditional economic load dispatch (NELD) problem. Unlike traditional economic load dispatch (TELD), generating sources in NELD are diversified with different types, including thermal, wind, and solar power plants. The reduction of total fuel consumption from thermal power plants is the main objective of this study. The Salp swarm algorithm and Northern Goshawk optimization are utilized to find the optimal solution for NELD. The evaluation of the real performance of these optimization tools is tested on the power system with twenty thermal power plants, two wind power plants, and one solar power plant. In addition, the power system must satisfy load demand variation within 24 hours per day as in practice. Northern Goshawk optimization outperforms Salp swarm optimization on all comparison criteria with no violation of involving constraints and minimum total fuel consumption. Therefore, Northern goshawk optimization is highly recommended for solving the NELD problem.

Keywords: New variant of traditional economic load dispatch (NELD), salp swarm algorithm, northern goshawk optimization, thermal generator, renewable energies, load demand variation

INTRODUCTION

One of the most considered problems in power system operation is economic load dispatch (ELD). The discovery of an optimal solution to the ELD problem can benefit both the economic and environmental sides [1]. In the past, traditional economic load dispatch (TELD) only focused on satisfying load demand at one hour. Thermal power plants are the unique source that is responsible for generating electricity. But now, the suggestion of new economic load dispatch (NELD) in this study considers the contribution of renewable energies and load demand variation [2–4]. Besides, minimization of total fuel consumption and shortening total emissions are two objective functions that are commonly considered while solving both TELD and NELD. The contribution of renewable energies such as wind and solar in NELD helps thermal power plants reduce their pressure at peak load times substantially [5, 6]. By acknowledging the positive contributions of RESs, we aim to solve the NELD problem in this study.

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The complicated degree of NELD over TELD is substantially increased in both scale and the number of related constraints. Therefore, meta-heuristic algorithms are acknowledged to be the best-applied method for solving NELD problems. The application of meta-heuristic methods for solving ELD problem in previous studies can be listed such as Hybrid grey wolf optimizer [7], Distributed roust optimization (DRO) [8], The improved bird swarm optimization [9], The particle swarm optimization with simplex search method (SSM-PSO) [10], The improved Manta ray optimization (IMRO) [11], An improved version of particle swarm optimization name quantum particle optimization (QPSO) [12], The improved firework algorithm (IFA) [13], differential evolution (DE) in [14], hurricane optimization (HO) and sine-cosine optimization (SCO) in [15], Grey wolf optimal [16], Salp swarm optimization [17], the Artificial algae algorithm (AAA) in [18], Particle swarm optimization is implemented in [19], Genetic algorithm (GA) [20], The combination of genetic algorithm (GA), Pattern search (PS) and Sequential quadratic programing in [21], Double-weighed particle swarm optimization (DW-PSO) [22], the Improved bacterial foraging algorithm (IBFA) [23], PSO with jumping time-varying acceleration coefficient (PSO-JTVAC) [24], Nondominated sorting genetic algorithm II (NSGA) [25], Chaotic differential evolution (CDE) [26], biogeography-based optimization (BBO) [27] and [34], Ameliorated dragonfly algorithm (ADA) [28]. Shuffled frog leaping algorithm, the Modified shuffled frog leaping algorithm and Global-best harmony search (GHS) [29], High-Performance Stochastic Fractal Search Algorithm [30], Improved Jaya algorithm [31], Effective cuckoo search algorithm [32], the original version of Stochastic fractal search algorithm [33], The hybrid swarm intelligence based Gravitational search algorithm [35], and Effective modified Firefly algorithm [36]. The contribution of meta-heuristic should be acknowledged the crucial element to the success of these studies.

In this study, we implement the Salp swarm algorithm (SSA) [39] and Northern Goshawk optimization (NGO) [40] to find the optimal solution for the NELD problem. Besides, the contributions of two wind and one solar power plant are incorporated into the power system to meet the load variation within a day of 24 hours. The main objective function of the whole study is to minimize total fuel consumption as much as possible.

The main contributions of the study can be summarized below:

- Find out the optimal solution to the NELD problem considering the contribution of both wind and solar energy profitably.
- Load variation within a day of 24 hours is considered successful while solving the NELD problem.
- Present a clear comparison of the performance of both SSO and NGO by particular witnesses, then point out the best-applied method for dealing with the NELD problem.

The study is built as follows: Section 1 is the Introduction, Section 2 is the problem formulation, Section 3 is the applied methods, Section 4 is the number of results, and Section 5 is the conclusions.

PROBLEM FORMULATION

Objective Function

The mathematical expression of the objective function is presented below:

$$\text{Minimizing TFC} = \sum_{n=1}^{N_{TG}} FC_n \tag{1}$$

Where N_{TG} is the quantity of thermal power plant; FCn is the fuel consumption of thermal power plant n, and FCn is calculated by:

$$FC_n = \mu_n + \pi_n TP_n + \rho_n TP_n^2 \text{ with } n = 1, \dots, N_{TG} \tag{2}$$

Where μ_n, π_n, and ρ_n are fuel consumption factors, and TPn is the active power supplied by thermal power plant n.

Constraints

Two main constraints must be strictly considered while solving both TELD and NELD. They are the power balance constraint and the generator working constraint. The formulation of these constraints will be expressed below:

- *Power balance constraint:* This constraint means that total active power supplied by all generating sources must be equal to the total power required by the load and total power loss in transmission lines. The expression of this constraint is shown below [37]:

$$PR + PL = \sum_{n=1}^{N_{TG}} TP_n + WP + SP \quad (3)$$

where PR is the power demand required by the load, PL is the total power loss in transmission lines; $\sum_{n=1}^{NTG} TP_g$ is total active power supplied by the thermal power plant, and WP and SP are active power supplied by wind and solar power plants.

The PL in Equation (3) is calculated by using Equation (4) below:

$$PL = \sum_{n=1}^{N_{TG}} \sum_{m=1}^{N_{TG}} TP_n B_{nm} TP_m + \sum_{n=1}^{N_{TG}} B_{0n} TP_n + B_{00} \quad (4)$$

Where, B_{gm}, B_{0n}, and B_{00} are loss factors, and TPn and TPm are power injected by the generators n and m.

- *Generator working constraints:* This constraint means that the value of active power produced by the thermal power plant must locate inside the boundaries of the minimum and maximum values:

$$TP_{n,min} \leq TP_n \leq TP_{n,max} \quad (5)$$

Where $TP_{n,min}$ and $TP_{n,max}$ are the working limitations of generator n.

- *Solar generator operation constraints:* according to [38], the rated power output of a solar generator (SP) is not greater than 80 % of the total load demand. Besides, the value of power output is also allowed to vary between the minimum and maximum values. The formula of the constraint is presented as follows:

$$\sum_{Z}^{N_{SG}} SP_Z \leq 80\% \times PR \quad (6)$$

$$SP_Z^{min} \leq |SP_Z| \leq SP_z^{max} \quad (7)$$

Where $\sum_{z}^{N_{SG}} SP_Z$ is the total active power generated by all solar generators; SP_Z is active power produced by solar generator z; SP_z^{min} and SP_z^{max} are the minimum and maximum values of power output supplied by solar generator z.

THE METHODS

In this section, two meta-heuristic methods are introduced for solving the NELD problem, including the Salp Swarm Algorithm (SSA) [39] and Northern Goshawk Optimization (NGO) [40]. SSO was proposed in mid-2017, while NGO was published at the end of 2021. These methods are all inspired by the swarm practices of animals in nature. Being meta-heuristic algorithms, the main difference between them is the update mechanism, which will be shown in the next subsections below:

The Salp Swarm Optimization

The update process for new solutions of SSA is conducted in two phases, including the update for the leader group and follower group. These phases are formulated by equations (8) and (10) below:

- *Phase 1:* The update for members of the leader group This phase is formulated by equation below:

$$SL_i = \begin{Bmatrix} Fi_i + Rd_1\big((Ub_i - Lb_i)Rd_2 + Lb_i\big)Rd_3 \geq 0 \\ Fi_i - Rd_1\big((Ub_i - Lb_i)Rd_2 + Lb_i\big), Rd_3 < 0 \end{Bmatrix} \quad (8)$$

Where SL_i is the new position of the leader i; Fi_i is the position of the food source; Rd_1 is the equalizer factor calculated by Equation (9), Rd_2 and Rd_3 are random values between 0 and 1; Ub_i and Lb_i are the upper and lower boundaries of the search space.

$$Rd_1 = 2e^{-\left(\frac{4It}{It^{max}}\right)^2} \tag{9}$$

where It is the current iteration and It^{max} is the maximum quantity of iteration.

- *Phase 2:* the update for the members of the follower group the description of this phase is described as follows:

$$FL_k = \frac{1}{2}(FL_k + FL_{k-1}) \tag{10}$$

Where FL_k and FL_{k-1} are the followers k and k-*1*

The Northern Goshawk Optimization (NGO)

Similar to SSA, the update process of NGO must go through two stages, including the Target positioning and Attack procedures. These stages are formulated below:

- *Stage 1:* Target positioning

The mathematical expression of this stage is expressed below:

$$x_{j,k}^{new\ 1} = \begin{Bmatrix} x_{j,k} + Rn_1(y_k - Rn_2 x_{j,k}), F_{SL} < F_j \\ x_{j,k} + Rn_1(x_{j,k} - y_k), F_{SL} \geq F_j \end{Bmatrix}; k = 1, \ldots K\&j = 1 \tag{11}$$

Where, $x_{j,k}^{new\_1}$ and $x_{j,k}$ are the k^{th} new and old variables of j^{th} solution; y_k is the k^{th} variable of the selected solution SL and $k = 1\ldots K$ where K is the quantity of the dimensions; Rn_1 is a random number in the interval between 0 and 1; Rn_2 is a natural random number, either 1 or 2; and F_{SL} is the fitness value of the selected solution SL. Po is the population size.

- *Stage 2:* Attack procedure

This stage is conducted by applying the equation below:

$$x_{j,k}^{new\_2} = x_{j,k} + PAZ(2Rn_1 - 1)x_{j,k} \tag{12}$$

Where, $a_{j,k}^{new\_2}$ is the k^{th} new variable owned by the j^{th} solution in the population; and PAZ is the possible active zone formulated as

$$PAZ = 0.02\left(\frac{It}{IT^{max}}\right) \tag{13}$$

Where, It and IT^{max} are the current value of iterations and the maximum number of iterations, respectively.

RESULTS

The study was carried out on a personal computer with a central processing unit (CPU) of 2.0 GHz and 8 GB of random access memory (RAM). The MATLAB programing language is the basic environment to conduct the whole coding. The results of the ELD will be organized by two cases, including TELD-fixed load demand and NELD-dynamic load demand. In the first section, we applied three meta-heuristic algorithms, including Particle swarm optimization (PSO) [41], Salp swarm algorithm (SSA), and Northern Goshawk optimization (NGO), to solve TELD with fixed load demand, identifying the best-applied method. The application of PSO in this section is aimed at showing the differences between the classical and modern meta-heuristics of their performance. In the second subsection, we applied the best method to find the optimal solution for NELD with dynamic load demand within a day of 24 hours.

Case 1: TELD-Fixed Load Demand

In the section, load demand is fixed at 2500 MW. Besides, the contribution of renewable energy sources is not considered in this case. The control parameters of the three applied methods about population size, the highest value of iteration, and the number of independent runs are 20, 200, and 50, respectively.

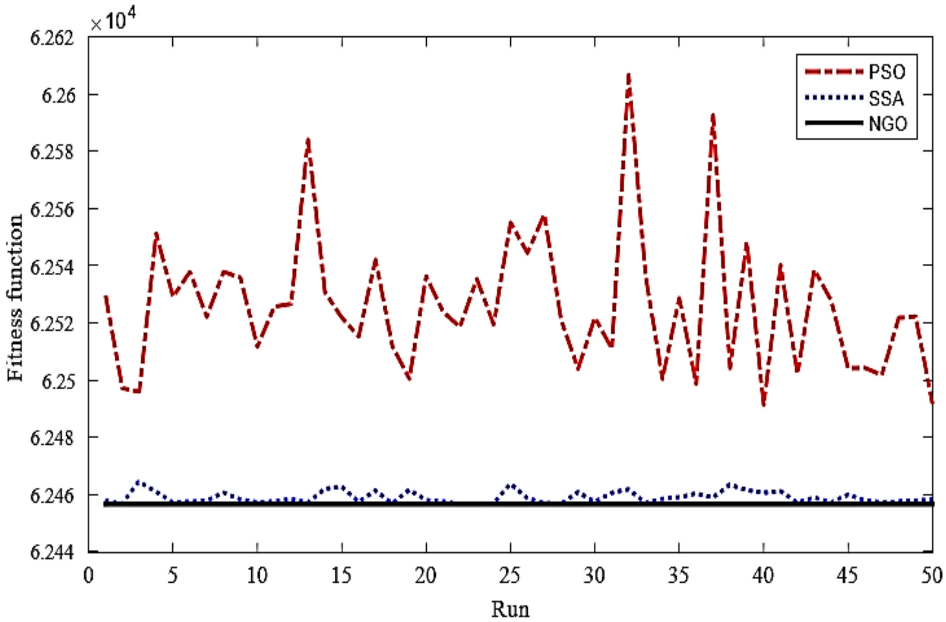

Figure 1. The results given by three applied methods after 50 independent runs.

In Figure 1, the red, blue, and black lines represent the optimal results of PSO, SSA, and NGO, respectively. PSO is the lowest effective method among the three applied ones, while NGO outperforms both PSO and SSA by reaching more optimal values during 50 independent runs.

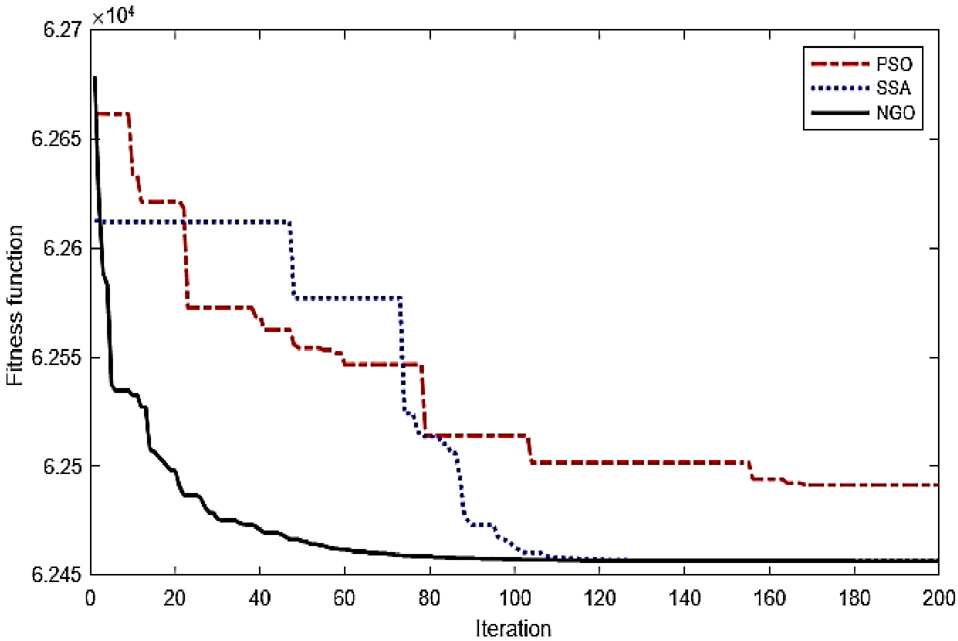

Figure 2. The best convergences of three applied methods among 50 independent runs

In Figure 2, NGO is the fastest applied method by only utilizing approximately 100 iterations to reach the optimal value. SSA requires over 130 iterations to do the same, while PSO cannot reach the optimal value even if the last iteration is used.

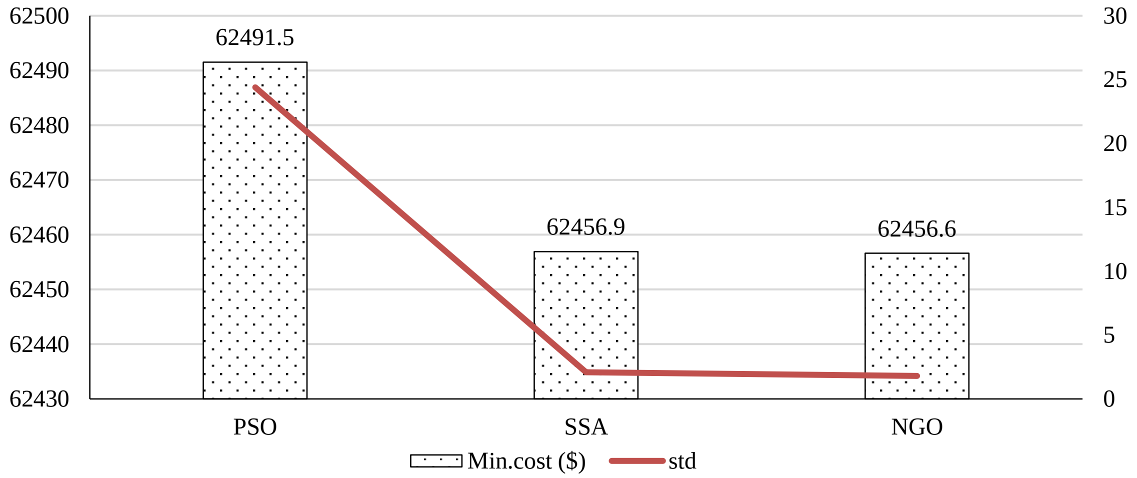

Figure 3. The comparison of Minimum TFC and standard deviations of three methods

Figure 3 reports the minimum TFC (Min.cost) and standard deviation (std). While these values of NGO are only 62456,6 ($) and 0.1, those of PSO are respectively 62491.5 ($) and 24.4. Clearly, NGO not only reaches the better optimal Min.cost but also proves itself the most stable method. Hence, NGO is considered the most effective method among the three applied ones. Moreover, the result of TFC reached by NGO is also compared with other previous research. This comparison is presented in Table 1.

Table 1. The comparison of TFC reported by NGO and previous research.

Methods	Minimum TFC ($/h)	Population size	Maximum Iteration
SFS [33]	62456.6331	10	250
BBO [34]	62457.5515	50	300
PSOGSA [35]	62456,63309	100	500
FA [36]	62458.881	10	1000
MFA [36]	62456.633	10	200
NGO	62456.6	20	200

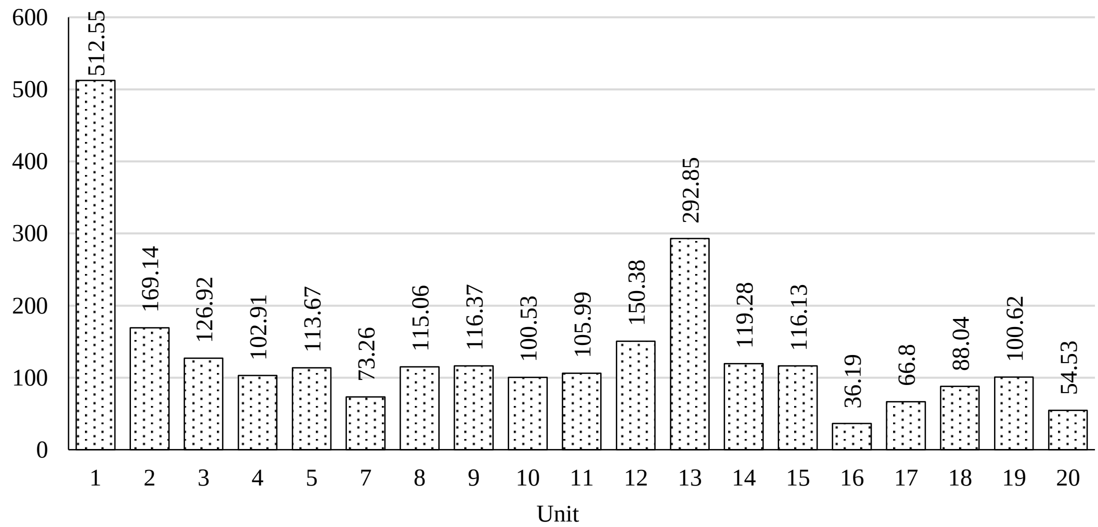

Figure 4. The power output of 20 thermal power plants.

In Figure 4, the power output values of 20 thermal power plants determined by NGO are shown.

Case 2: NELD-Dynamic Load Demand
In this case, the tested power system is modified with twenty thermal power plants, one solar power plant, and two wind power plants. The power output of wind and solar power plants during a day is presented in Figure 6 according to [42] and [43]. Besides, it is supposed that the variation of load demand within a day is followed in Figure 5.

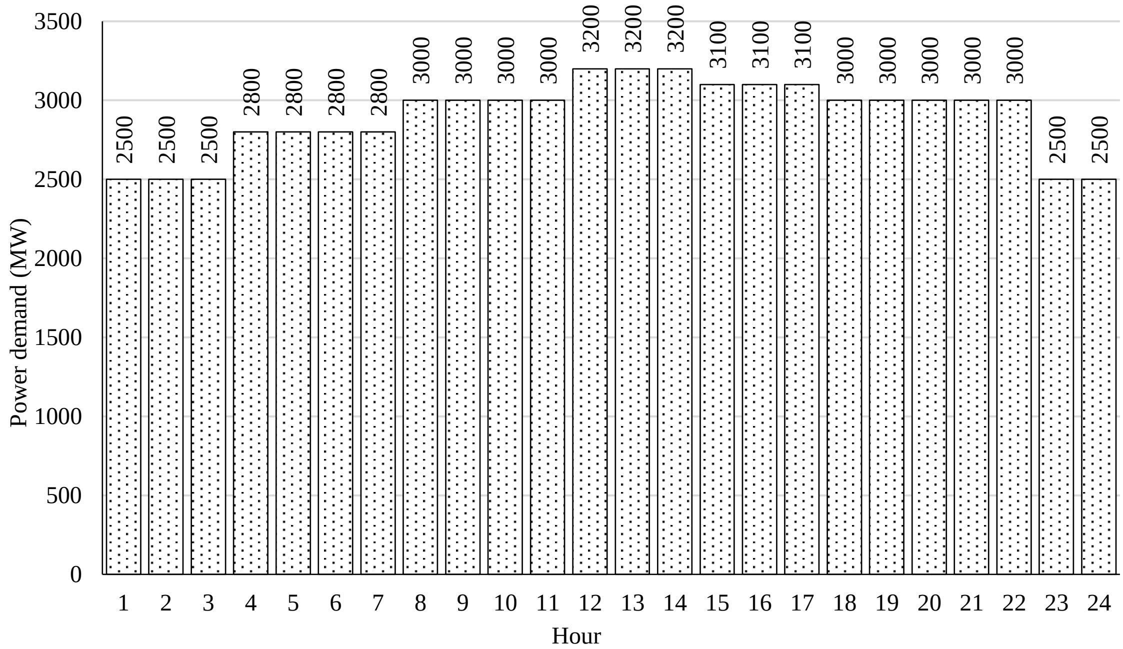

Figure 5. Load demand within a day with 24 hours.

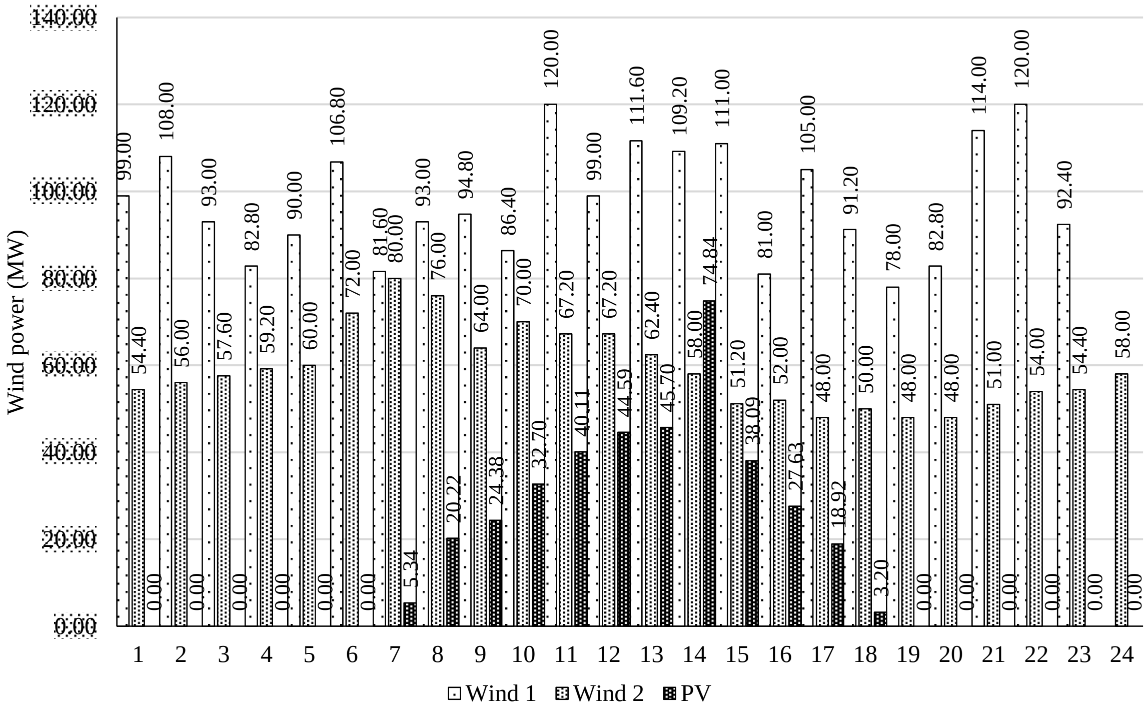

Figure 6. Power output supplied by solar power plant.

In Figure 6, the power output from two wind power plants is uninterrupted within a day, while the solar power plant can only supply power from 7 a.m. to 18 p.m.

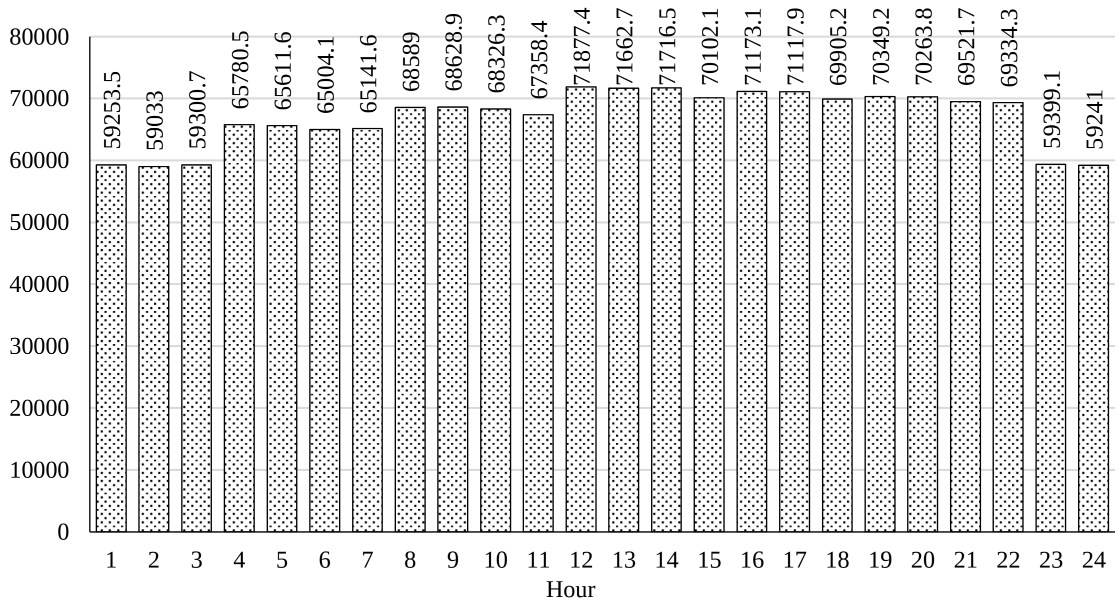

Figure 7. The TFC values during 24 hours obtained by NGO.

Figure 7 shows the optimal values of TFC in each hour within 24 hours per day. Besides, the power output of 20 thermal power plants at each hour will be reported in Table 2 and Table 3.

Table 2. The power output (MW) of the thermal power plant 1 to 10 in 24 hours.

Hour\ Unit	1	2	3	4	5	6	7	8	9	10
1	481.2	148.0	113.7	93.3	107.5	66.2	112.7	107.5	93.8	99.8
2	478.8	145.8	112.4	92.9	107.0	65.8	112.4	106.6	93.4	99.7
3	481.6	147.0	113.7	93.4	107.6	66.8	112.8	107.7	93.8	100.9
4	545.5	190.3	140.6	112.6	120.2	80.8	117.8	125.6	107.1	113.2
5	543.5	190.9	140.2	112.2	119.9	80.1	117.3	125.3	107.1	111.1
6	537.5	186.4	137.6	110.5	118.8	78.9	117.0	123.5	105.8	110.8
7	539.4	187.1	138.1	111.1	118.7	79.3	117.5	123.9	106.2	111.1
8	573.8	200.0	153.2	120.9	125.9	86.9	121.6	134.3	114.2	121.1
9	574.6	200.0	152.7	121.2	126.4	87.3	121.2	134.4	114.3	120.6
10	571.4	200.0	151.8	120.3	125.5	86.9	120.9	133.4	113.0	120.0
11	560.6	200.0	146.6	117.0	123.2	84.0	119.1	130.4	111.2	116.2
12	600.0	200.0	165.7	130.5	132.7	94.2	124.9	146.9	123.5	135.1
13	599.7	200.0	164.7	130.1	132.7	94.9	123.6	143.0	121.5	136.4
14	600.0	200.0	167.4	131.5	134.8	96.9	125.0	144.1	119.9	136.5
15	591.6	200.0	159.5	126.1	129.6	90.4	123.2	139.3	117.6	126.1
16	599.8	200.0	163.2	130.8	131.2	94.0	124.8	143.0	119.3	132.0
17	599.6	200.0	163.1	128.2	131.9	93.9	125.0	142.5	118.5	132.5
18	588.6	200.0	158.6	125.7	128.7	90.8	123.5	138.8	116.7	126.2
19	593.0	200.0	160.2	126.2	129.8	91.9	123.8	139.9	117.5	128.7
20	592.6	200.0	159.8	125.5	130.1	92.1	123.3	139.7	117.6	127.1
21	584.1	200.0	156.8	124.1	128.2	89.8	122.6	137.6	115.9	124.2
22	582.2	200.0	156.0	123.4	127.8	88.7	122.2	136.6	115.5	123.7
23	482.3	148.5	114.2	93.9	107.7	67.0	113.1	107.9	93.6	100.2
24	481.1	147.3	113.6	93.2	107.3	66.9	112.9	107.6	93.6	100.2

Table 3. The power output (MW) of the thermal power plant 11 to 20 in 24 hours.

Hour\ Unit	11	12	13	14	15	16	17	18	19	20
1	147.4	286.8	115.2	30.3	108.3	35.6	59.6	80.9	94.7	47.3
2	147.3	286.1	115.0	30.2	108.0	35.7	59.5	80.3	94.1	47.1
3	147.6	287.0	115.1	30.6	108.5	35.8	59.7	81.0	94.6	47.6
4	153.5	298.7	123.2	31.8	123.5	36.9	74.3	95.3	107.2	61.8
5	153.2	298.3	123.3	31.8	123.6	36.7	73.7	95.2	106.9	61.0
6	152.6	297.3	122.4	31.8	121.5	36.7	72.5	93.7	105.6	59.6
7	152.3	298.0	122.3	30.5	122.1	36.6	72.9	93.6	106.0	60.7
8	155.6	304.3	126.3	32.8	129.7	37.2	80.8	100.9	113.1	68.3
9	155.4	304.0	126.4	33.3	130.1	37.4	81.3	101.4	112.9	68.0
10	155.7	303.4	126.0	32.9	129.2	37.2	80.3	100.4	112.2	67.2
11	154.0	301.9	125.1	32.9	127.2	37.2	77.6	98.6	110.6	65.7
12	159.4	311.2	129.5	36.7	140.0	38.2	85.0	111.3	119.9	80.3
13	162.2	313.1	130.8	35.9	136.7	38.0	85.0	109.0	119.9	77.5
14	163.4	308.2	130.0	36.9	136.3	38.1	85.0	107.3	119.1	76.7
15	156.0	307.5	128.1	33.8	133.3	37.7	84.2	104.5	117.3	70.7
16	160.3	308.4	128.6	35.4	136.3	38.3	85.0	106.9	117.7	75.1
17	159.6	308.5	129.2	36.2	135.5	37.9	85.0	106.9	118.2	75.4
18	157.0	306.3	127.7	32.3	133.4	37.5	84.2	103.7	115.2	71.6
19	157.3	307.6	128.2	34.9	133.9	37.7	85.0	104.1	116.6	72.5
20	156.8	307.6	128.5	34.8	134.5	37.7	84.7	104.0	116.3	72.2
21	156.3	305.7	127.2	33.8	132.3	37.3	83.5	102.9	115.0	70.2
22	156.0	305.7	127.3	34.2	131.7	37.3	82.9	102.1	114.9	69.9
23	147.7	287.3	115.3	29.9	108.9	35.8	59.8	81.3	94.9	47.8
24	147.5	286.8	115.0	30.3	108.4	35.7	59.9	80.5	94.5	46.8

CONCLUSION

In this study, two novel meta-heuristic methods, including Salp swarm algorithms (SSA) and Northern goshawk optimization (NGO) are applied successfully to solve both TELD and NLED. In particular, in TELD, load demand is the fixed value, and the thermal power plant is the only generating source, while in NELD, the variation of load demand with the day is considered, and the contribution of wind and solar energy is both evaluated. The NGO proved itself to be the most capable method for reaching better optimal solutions and providing stable performance than PSO and SSA. Specifically, among the three applied methods, NGO can achieve better TFC value, provide stable performance, and fast convergence to optimal results. Therefore, NGO has acknowledged the powerful search method for dealing with NELD. In the future, NELD should be expanded by considering more complicated constraints such as multiple fuels, ramp-rated, and prohibited operation constraints, etc. Besides, NGO is also suggested to be modified to reach higher performance.

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