A hunger game search algorithm for economic load dispatch

Widi Aribowo, Supari, Bambang Suprianto
Department of Electrical Engineering, Universitas Negeri Surabaya, Surabaya, Indonesia

Article Info

Article history:

Received Aug 9, 2021
Revised Jan 31, 2022
Accepted Feb 20, 2022

Keywords:

Economic load dispatch
Hunger games search
Metaheuristic
Optimization

ABSTRACT

This work proposes a new approach to solve the economic load dispatch (ELD) issue in power systems by metaheuristic algorithms inspired by natural life. The problem to be resolved is to optimize the power system network with various constraints by considering the cutting in the cost of the resulting in the transmission of the electric system. The method used in this study is the hunger games search (HGS). This method duplicates the hunger-driven activity and the animal's choice of behavior. The proposed method is to add the concept of starvation as a process structure. Adaptive weights based on the concept of hunger are designed and used to simulate the effects of hunger on each trace process. To get the performance of the proposed method, this research uses mathematical methods, particle swarm optimization (PSO), differential evolution (DE), giza pyramids construction (GPC), and sine tree-seed algorithm (STSA) as a comparison. This study uses 2 case studies. In case study 1, the proposed method has a 0.16% better cost of generation than the mathematical method. Comparison of the HGS method with the PSO method in the second case study, it was found that the HGS method was 0.018% better than the PSO. From the research, it was found that the HGS method was superior.

Corresponding Author:

Widi Aribowo
Department of Electrical Engineering, Universitas Negeri Surabaya
Unesa Kampus Ketintang, Surabaya 61256, Jawa Timur, Indonesia
Email: widiaribowo@unesa.ac.id

1. INTRODUCTION

In the operation of the generating system, a small percentage change can cause a change in costs. In an electric power operating system, the largest cost component is the cost of fuel. Technological developments, the increasing demand for electric power and the cost of production fuel prices, these push the economic load dispatch (ELD) to play an important role. It aims to optimize the best location for all generating units in the system, meeting the power requirements required by taking into account the lowest possible fuel production and operating costs. In addition, it removes all restrictions on the operation of the power system [1]. The purpose of ELD is to minimize the cost of generation in the electric power system [2]. Models and types of problems that are diverse and complex. This makes eld very nonlinear especially for large systems [3].

Clever and precise ELD completion of thermal generators has the advantage of reducing operating costs and increasing system reliability to a greater extent. Besides, it has a low affect on the environment [4]. ELD problems can be solved using classical mathematical modeling and equations. The input-output characteristic or cost function of the generating system is modeled in such a way as a mathematical method [5].

Several classical approaches in ELD optimization have been proposed by several researchers. Takeang and Aurasopon [6] conducted a study using a hybrid method combining lambda iteration and simulation annealing method (MHLSA) to solve the economic delivery (ED) problem with the characteristics of a smooth cost function. Chauhan [7] used the lambda iteration method to solve the economical load dispatch problem for 6 generating unit frames with and without transmission loss. Xing *et al.* [8] presented the distributed augmented lambda-iteration method to solve ELD problems. Tang *et al.* [9] propose a Lagrangian relaxation with an incremental proximal algorithm to tackle the dispatch problem. Tang *et al.* [9] integrate the stead of Lagrangian relaxation, which allows the issue to be decomposed into a large number of smaller problems and the proximal method, which leads to much faster convergence. Lai *et al.* [10] present a dynamic multiplier Lagrangian relaxation approach as a multi-area economic dispatch (MAED) solution in a fully decentralized manner. A dynamic multiplier refers to a multiplier that is related to the power balance mathematical equation of the tie-line bus in each area. Parallel Augmented Lagrangian Relaxation method introduced by Ding *et al.* [11]. The parallel augmented Lagrangian relaxation method is a Dynamic economic dispatch (DED) model which is broken down into several single period economic delivery models that can be efficiently handled in parallel. Mclarty *et al.* [12] present a solution to the economic dispatch problem using a complementary convex square optimization. Xu *et al.* [13] presented an economic delivery strategy for micro networks based on the sequential quadratic programming (SQP) method. Hoke *et al.* [14] applied a fast and reliable linear programming (LP) approach to the economic dispatch of network-bound microgrids containing one or all of the resources. Some of the obstacles experienced by the classical method are nonlinear and complex ELD problems.

Some researchers are increasingly popular by introducing several artificial intelligence methods, especially the metaheuristic algorithm. Several metaheuristic methods were introduced to solve real problems including the problem of economic load dispatch. A memory-based gravitational search algorithm (MBGSA) presented by Younes *et al.* [15]. This method uses an MBGSA for solving the economic load dispatch in a micro-grid. The MBGSA method adopts the concept of Newton's law of gravity in storing the best agent solution from the last iteration to get a new agent. Deb *et al.* [16] used the gradient-based optimizer (GBO) method to solve ELD problems. The performance of GBO in ELD is tested using various scenarios such as ELD with transmission losses, combined economic and emission dispatch (CEED), and CEED with valve point effects. Basu uses the squirrel search algorithm (SSA) method to solve the complex multi-region combined economy and thermal energy delivery problem with the integration of renewable energy sources [17]. Srivastava and Das [18] present the Kho-Kho optimization method to solve the combined emission economic dispatch and combined heat and power economic dispatch problem. This method is inspired by the strategy used by players in the famous tag team game played in India, namely Kho-Kho. Arezki and Williams [19] presented a combination of the cuckoo optimization algorithm method with a penalty function and a binary approach to solving the problem of non-linear and non-convex combined energy and heat transfer (CHPED).

This paper will investigate the potency of the newest metaheuristic methods, namely, hunger games search (HGS) to solve ELD problems. HGS was developed by Heidari *et al.* [20]. The HGS method has several advantages, namely a simple algorithm and excellent convergence capability. So that the optimal solution is obtained. This is validated by an analysis that uses comparisons with other methods with 23 mathematical functions tested at the IEEE CEC 2014. This paper uses 2 case studies, namely using 3 and 6 units of power system based on the constraints experienced. ELD problem solving has become popular because many new methods are found to be applied to optimize solutions to ELD problems. Several researches and papers on ELD with several methods have been presented. However, there is still a lot of room to be explored to find the best solution. This paper is structured: the second session presents an ELD study and a brief description of the HGS. The third session describes the results and analysis of the metaheuristic methods used. The final section presents the conclusions of this paper.

2. RESEARCH METHOD

2.1. Economic load dispatch

In this session, the ELD mathematical formulas are presented in detail. In addition, appropriate descriptions of how to use the inequality constraint, the equality constraint, and the cost function are provided. Evaluation of the ELD problem is aimed at obtaining the optimal value of the economic cost of the electric power grid in various conditions. This is to get a solution to reduce the total cost of fuel consumption. This can be formulated in the (1)-(5):

$$M(Ft) = \sum_{k=1}^{n} F_k(P_k) = \alpha_k {P_k}^2 + \beta_k P_k + \gamma_k \tag{1}$$

where Ft is the total cost in *R/h*. F_k Is the cost function of the ith generating unit. P_k is *k*-th the generator fuel cost. α_k, β_k and γ_k are the the weight parameter. The total power produced is equivalent to the amount of load demand (P_D) and all power losses (P_L). This can be formulated in (2):

$$\sum_{k=1}^{n} P_k - P_D - P_L = 0 \tag{2}$$

$$P_L = \sum_{j=1}^{n} \sum_{k=1}^{n} P_j B_{jk} P_k \tag{3}$$

where P_j and P_k are the real power generations at the j th and k th buses. B_{jk} is the paramter of losses. The power generated by the generator must be between its rating (*pmin* and *pmax*). The limits for each generator can be written:

$$P_k{}^{min} \le P_k \le P_k{}^{max}\ (i = 1, \dots \dots . n) \tag{4}$$

where $P_k{}^{min}$ is the lowest limit of the k th generator output power. $P_k{}^{max}$ is the maximum output power of the k th generator. The cost function is required an estimate of the optimal power unit value while minimizing objective criteria (CF).

$$CF = \sum_{k=1}^{n} C_k(P_k) + \lambda \times abs(\sum_{k=1}^{n} P_k - P_D - P_L) \tag{5}$$

2.2. Hunger games search (HGS)

The HGS algorithm is developed with a mathematical model that is limited by activities that are driven by hunger and choice behavior. It is developed with a simple concept and pays attention to the most efficient performance.

2.2.1. Approach food

Individual cooperative communication and foraging behavior which is the basis of the HGS can be represented in (6)-(15):

$$\overrightarrow{S(t+1)} = \begin{cases} rule_1; \overrightarrow{S(t)} \cdot \big(1 + rand(1)\big), & r_1 < 1 \\ rule_2, \overrightarrow{W_1} \cdot \overrightarrow{S_b} + \overrightarrow{W_2} \cdot \vec{R} \cdot \left|\overrightarrow{S_b} - \overrightarrow{S(t)}\right|, & r_1 > l,\ r_2 < E \\ rule_3, \overrightarrow{W_1} \cdot \overrightarrow{S_b} - \overrightarrow{W_2} \cdot \vec{R} \cdot \left|\overrightarrow{S_b} - \overrightarrow{S(t)}\right|, & r_1 > l,\ r_2 < E \end{cases} \tag{6}$$

$$E = \operatorname{sech}(\,|Ft(i) - BFt|) \tag{7}$$

$$\operatorname{sech}(x) = \frac{2}{e^x + e^{-x}} \tag{8}$$

$$\vec{R} = 2\ \times shrink\ x\ rand - shrink \tag{9}$$

$$shrink = 2 \times (1 - \frac{t}{T_{max}}) \tag{10}$$

where $\overrightarrow{S(t)}$ is a notation indicating the area of each individual. r_1 and r_1 are the random numbers [0,1]. $rand$ is a random number that fits a normal allocation. t is the current iteration process. $\overrightarrow{W_1}$ and $\overrightarrow{W_2}$ are notations that indicate the weight of hunger. $\overrightarrow{S_b}$ is the best individual area. $\left|\overrightarrow{S_b} - \overrightarrow{S(t)}\right|$ is is a model of the existing range of individual activities. Multiplication by $\overrightarrow{W_2}$ as the stimulus that affects hunger in various activities. $\overrightarrow{S(t)} \cdot \big(1 + rand(1)\big)$ is denoting the workings of the agent looking for food at times of hunger and at random at currently. $Ft(i)$ is the fitness value of each individual. BFt is the best fitness gained in the current iteration process. T_{max} is the maximum number of iterations. Search algorithms can be divided into two types according to the source point, namely:

- Seeking on the basis of $\overrightarrow{S(t)}$
  In the first instruction, the algorithm is individualistic. They lack the cooperative spirit and cooperative phase. The focus is on voracious foraging.
- Seeking on the basis of $\overrightarrow{S_b}$
  This algorithm triggers cooperation among several entities as they search for food. This involves three factors, namely: $\vec{R}$, $\overrightarrow{W_1}$and, $\overrightarrow{W_2}$.

In (7) encourages individuals to explore optimally which can provide opportunities to find all locations to some extent.

2.2.2. Hunger role

Hunger method in the search space can be formulated mathematically:
The $\overrightarrow{W_1}$ and $\overrightarrow{W_2}$ notation of (7) are:

$$\overrightarrow{W_1} = \begin{cases} h(i) \cdot \frac{N}{Sh} \times r_4, & r_3 < l \\ 1 & ,r_3 > l \end{cases} \tag{11}$$

$$\overrightarrow{W_2} = (1 - \exp(-|h(i) - Sh|)) \times r_5 \times 2 \tag{12}$$

$$h(i) = \begin{cases} 0 & ,AF(i) == BF \\ h(i) + aH & ,AF(i)! = BF \end{cases} \tag{13}$$

$$TH = \frac{Fit(i) - BestFitness}{WorstFitness - BestFitness} \times r_6 \times 2 \times (Ub - Lb) \tag{14}$$

$$aH = \begin{cases} LH \ \ x \ (1 + r), & TH < LH \\ TH, & TH \geq LH \end{cases} \tag{15}$$

where $h(i)$ is the hunger of each individual. N is the amount of individual. Sh is the sum of the hungry sensings of all individuals. r_3, r_4 and r_5 are random numbers in the range of [0,1]. $AF(i)$ is maintenance of the fitness of each individual in the current iteration. In each iteration, the best value of individual hunger is set to 0. On the other hand, the new hunger (aH) is the sum based on the initial hunger. $Fit(i)$ is the fitness value of each individual. $estFitness$ is the best fitness value in the current iteration process. $WorstFitness$ is the worst fitness score in the current iteration process. UB and LB are notations that indicate the upper and lower boundaries of the search space. LH is the finite value of the lower bound of aH

3. RESULTS AND DISCUSSION

To obtain the performance of the proposed method, a set of known global optimal mathematical functions is used. The 19 functional benchmarks were used as a comparative test. The test was divided into 3 groups; unimodal, multimodal and composite. Each group has its own characteristics and strengths.

The unimodal function (F1-F7) is suitable for benchmarking algorithm exploitation because this function has one global optimal and no local optima. Figure 1 as shown in Appendix. The chart of unimodal function can be seen in Figure 1(a) to Figure 1(g). On the other hand, the multi-modal function (F8-F13) has a large number of local optima and is very helpful for checking exploration and subtracting the local optima position of the algorithm. The chart of multi-modal function can be seen in Figure 1(h) to Figure 1(m). The last one is a composite function. Composite function (F14-F19) is a combination of rotated, shifted, biased multi-modal test functions. The chart of composite function can be seen in Figure 1(n) to Figure 1(s). The function group of search space is interesting and full of challenges. It is affected the movement of the graph is very similar to the actual search space. It is useful for measuring performance in terms of exploration and exploitation.

Laptop with RAM specifications: 8 GB, Intel I5-5200 CPU: 2.19 GHz 64 bit is used as a test. The best performance of each algorithm is obtained by running it 50 times. The best results, average, worst and standard deviation of the total fuel value can be known, the algorithm uses a search agent 30. The ELD test uses 2 case studies, namely 3 power systems and 6 power systems. The study uses the power system specifications derived from the reference literature.

3.1. Case study with 3 power systems

In this research, case study 1 is a 3 unit power system. This is based on the ELD from used to explore the performance of the HGS in setting the optimal power generation set. In Table 1, it can be seen in detail from the specifications of the cost coefficient and generating capacity for the 3 thermal unit system used. The system are 3 thermal power systems identified as generators P1, P2, and P3. The power loss coefficient (ζ) of this system is also presented. Power requirement in test case 1 is PD=150 MW.

The estimated value of load, total power and power losses based on the giza pyramids construction (GPC), sine tree-seed algorithm (STSA) and HGS methods together with the results of the performance of the mathematical method are shown in detail in Table 2. It is obvious from Table 2 that the GPC, STSA and HGS methods generate a cost of \$ 1597.48152/hour, which is both worthwhile and acceptable. The total loss on optimal delivery using the HGS method is 152.34204 MW. Meanwhile, the total loss on optimal delivery using the STSA method is 152.3419. The generate a cost obtained using the GPC, HGS and STSA methods is relatively smaller than the mathematical method [24]. The mathematical method [24] has the same loss value for optimal delivery with the STSA method.

Table 1. Data 3 units power system

P_1 (MW)	α_i (\$/h)	β_i (\$/MW h)	Υ_i (\$/MW^2 h)	P_{min} (MW)	P_{max} (MW)
P_1	0.008	7.00	200	10	85
P_2	0.009	6.30	180	10	80
P_3	0.007	6.80	140	10	70

$$\zeta = \begin{bmatrix} 0.000218 & 0.000093 & 0.000028 \\ 0.000093 & 0.000228 & 0.000017 \\ 0.000028 & 0.000017 & 0.000179 \end{bmatrix}$$

Table 2. Assess output power of 3 unit power system with PD=150 MW

Generator output (MW)	Math method [21]	PSO[22]	DE[23]	GPC [24]	STSA[24]	HGS
P_1	33.4701	35.3084	32.796321	32.821883	32.817346	32.810133
P_2	64.0974	64.3204	64.605669	64.589653	64.582312	64.595079
P_3	55.1011	52.7259	54.940121	54.930498	54.942246	54.93683
PL (MW)	2.3419	2.35464	2.342110	2.3420344	2.3419047	2.3420421
Pi (MW)	152.3419	152.35464	152.342110	152.34203	152.3419	152.34204
PD MW)	150	150	150	150	150	150
Cost (\$/h)	1599.98	1597.58	1597.48152	1597.48152	1597.48152	1597.48152

3.2. Case study with 6 power systems

The second experiment is to use 6 units of power systems consisting of 6 units of thermal power plants. This experiment was carried out to get the value of the effectiveness of the method used in estimating the cost of generation and the performance of the method used. On the other hand, the main objective of this experiment is to obtain the approximate value of the power load of each unit. The specifications and details of the system with 6 thermal generating units tested with PD=1263 MW can be seen in Table 3. The power loss coefficient (ζ) of this system is also presented. The estimation results of load, power loss, total and cost and the cost of generating each unit of the power system in case study 2 with specifications of 6 thermal generating units can be seen in detail in Table 4. The proposed method, namely the HGS method, has the best value at the cost of generation. The value is 15442.6566 (\$/hour). This value is very thin with the DE method. Meanwhile, the total loss on this optimal delivery is 152.342110 MW. The worst cost of generation is owned when using the GPC method with a value of 15479.01406 (\$/hour).

Table 3. Assess output power of 6-unit power system with PD=1263 MW

Generator output (MW)	PSO [25]	DE [23]	GPC [24]	STSA [24]	HGS
P_1	440.576558	447.078451	416.6701414	444.6499234	447.0687489
P_2	167.43691	173.154524	200	171.7126716	173.1804998
P_3	278.235609	263.847013	300	261.1550089	263.9224149
P_4	150	139.144509	150	150	139.0512885
P_5	157.606137	165.610746	143.668211	162.7314736	165.5763871
P_6	81.224444	86.579146	64.93809964	84.95378805	86.61635311
PL (MW)	12.079658	12.414390	12.276452	12.202865	12.41569239
Pi (MW)	1275.079658	1275.414388	1275.2765	1275.2029	1275.4157
PD (MW)	1263	1263	1263	1263	1263
Cost (\$/h)	15445.48662	15442.6569	15479.01406	15444.0226	15442.6566

Difference in the value of the cost of generating the GPC method with the HGS method of 0.25%. Meanwhile, the value of the cost of generation from the STSA method is 0.009% lower than the HGS method. The results of best cost, average cost, worst cost, and standard deviation (STD), where they are calculated can be seen in Table 4. In Table 4, it can be seen that the proposed method, namely HGS, has a minimum cost of 15442.6566/hour. The average cost of the DE method is much better than the HGS method which is \$ 15444.996525/hour.

Table 4. Data 6 units power system

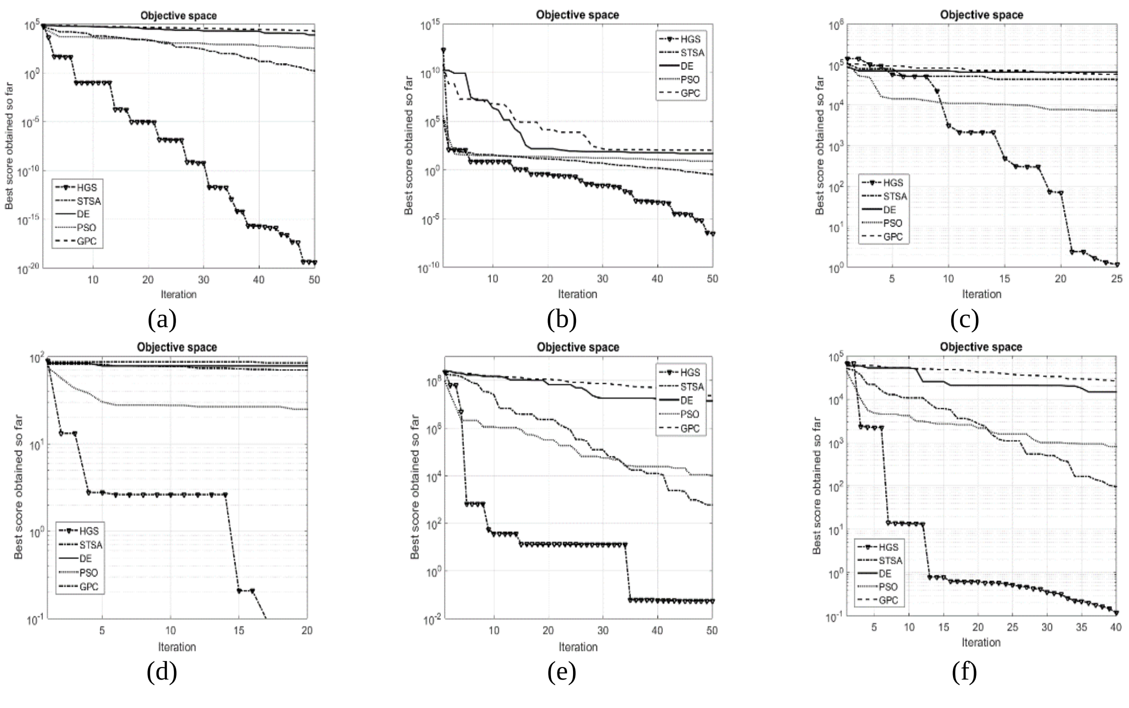
P_1 (MW)	α_i (\$/h)	β_i (\$/MW h)	Υ_i (\$/MW^2 h)	P_{min} (MW)	P_{max} (MW)
P_1	0.007	7.00	240	100	500
P_2	0.0095	10	200	50	200
P_3	0.009	8.5	220	80	300
P_4	0.009	11	200	50	150
P_5	0.008	10.5	220	50	200
P_6	0.0075	12	190	50	120

$$\zeta = 10^{-3} \times \begin{bmatrix} 0.017 & 0.012 & 0.007 & -0.001 & -0.005 & -0.002 \\ 0.012 & 0.014 & 0.009 & 0.001 & -0.006 & -0.001 \\ 0.007 & 0.009 & 0.031 & 0 & -0.01 & -0.006 \\ -0.001 & 0.001 & 0 & 0.024 & -0.006 & -0.008 \\ -0.005 & -0.006 & -0.010 & -0.006 & 0.129 & -0.002 \\ -0.002 & -0.001 & -0.0060 & -0.008 & -0.02 & 0.15 \end{bmatrix}$$

4. CONCLUSION

In this research, the effective solution to the economic load dispatch (ELP) problem has been explored using a metaheuristic algorithm, namely the HGS. The proposed method was explored and tested using three and six power generating units. This study uses mathematical methods, particle swarm optimization (PSO), differential evolution (DE), giza pyramids construction (GPC), and sine tree-seed algorithm (STSA) as a comparison to determine the performance of the proposed method. The result is that the proposed method has outperformed other comparative methods. The HGS-based method has proven to be optimal in achieving the optimal power load combination in the power system, with critical issues to meet ELD constraints and achieve minimum fuel costs. The HGS method has a very thin generation cost and transmission loss with the DE method in 2 case studies. The generation cost of the proposed method in case study 1 is 0.16% better than the mathematical method. Meanwhile, the generation cost of the proposed method is 0.0061% better than the PSO method. The generation cost of the DE, GPC, STSA and HGS methods has the same value, namely 1597.48152 (\$/h). In the second case study, the cost of generating the HGS method is better than the DE, GPC, and STSA methods.

APPENDIX



(a) (b) (c)

(d) (e) (f)

Figure 1. The convergence curve of benchmark function (a) F1, (b) F2, (c) F3, (d) F4, (e) F5, (f) F6

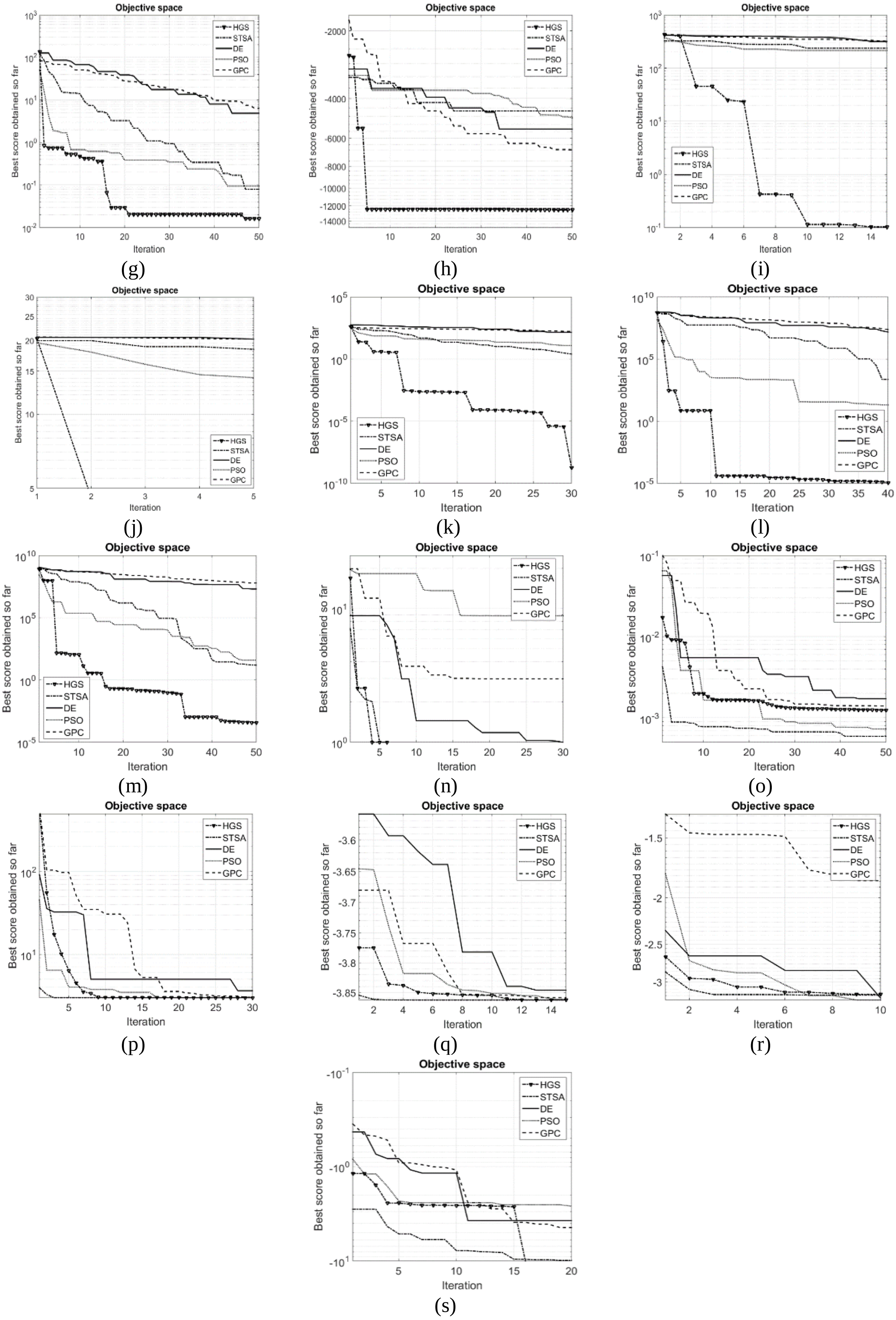


Figure 1. The convergence curve of benchmark function (g) F7, (h) F8, (i) F9, (j) F10, (k) F11, (l) F12, (m) F13, (n) F14, (o) F15, (p) F16, (q) F17, (r) F18, (s) F19 *(continue)*

REFERENCES

[1] W. Aribowo, B. Suprianto, I. G. P. Asto Buditjahjanto, M. Widyartono, and M. Rohman, "An improved neural network based onparasitism – predation algorithm for an automatic voltage regulator," *ECTI Transactions on Electrical Engineering, Electronics, and Communications*, vol. 19, no. 2, pp. 136–144, Jun. 2021, doi: 10.37936/ecti-eec.2021192.241628.

[2] H. S. Maharana and S. K. Dash, "Dual objective multiconstraint swarm optimization based advanced economic load dispatch," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 3, pp. 1924–1932, 2021, doi: 10.11591/ijece.v11i3.pp1924-1932.

[3] A. T. Doan, D. T. Viet, and M. Q. Duong, "Economic load dispatch solutions considering multiple fuels for thermal units and generation cost of wind turbines," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 5, pp. 3718–3726, Oct. 2021, doi: 10.11591/ijece.v11i5.pp3718-3726.

[4] R. Habachi, A. Boulal, A. Touil, A. Charkaoui, and A. Echchatbi, "Economic and emission dispatch using cuckoo search algorithm," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 5, pp. 3384–3390, Oct. 2019, doi: 10.11591/ijece.v9i5.pp3384-3390.

[5] P. Surekha and S. Sumathi, "Solving economic load dispatch problems using differential evolution with opposition based learning," *WSEAS Transactions on Information Science and Applications*, vol. 9, no. 1, pp. 1–13, 2012.

[6] C. Takeang and A. Aurasopon, "Multiple of hybrid lambda iteration and simulated annealing algorithm to solve economic dispatch problem with ramp rate limit and prohibited operating zones," *Journal of Electrical Engineering and Technology*, vol. 14, no. 1, pp. 111–120, Jan. 2019, doi: 10.1007/s42835-018-00001-z.

[7] G. Chauhan, A. Jain, and N. Verma, "Solving economic dispatch problem using mipower by lambda iteration method," in *Proceedings - 1st International Conference on Intelligent Systems and Information Management, ICISIM 2017*, 2017, vol. 2017-Janua, pp. 95–99, doi: 10.1109/ICISIM.2017.8122155.

[8] H. Xing, Z. Lin, and M. Fu, "Distributed augmented lambda-iteration method for economic dispatch in smart grid," in *Proceedings - 2017 Chinese Automation Congress, CAC 2017*, 2017, vol. 2017-Janua, pp. 3302–3307, doi: 10.1109/CAC.2017.8243347.

[9] C. Tang, J. Xu, Y. Tan, Y. Sun, and B. Zhang, "Lagrangian relaxation with incremental proximal method for economic dispatch with large numbers of wind power scenarios," *IEEE Transactions on Power Systems*, vol. 34, no. 4, pp. 2685–2695, 2019, doi: 10.1109/TPWRS.2019.2891227.

[10] X. Lai, H. Zhong, Q. Xia, and C. Kang, "Decentralized intraday generation scheduling for multiarea power systems via dynamic multiplier-based lagrangian relaxation," *IEEE Transactions on Power Systems*, vol. 32, no. 1, pp. 454–463, 2017, doi: 10.1109/TPWRS.2016.2544863.

[11] T. Ding and Z. Bie, "Parallel augmented lagrangian relaxation for dynamic economic dispatch using diagonal quadratic approximation method," *IEEE Transactions on Power Systems*, vol. 32, no. 2, pp. 1115–1126, 2017, doi: 10.1109/TPWRS.2016.2576465.

[12] D. McLarty, N. Panossian, F. Jabbari, and A. Traverso, "Dynamic economic dispatch using complementary quadratic programming," *Energy*, vol. 166, pp. 755–764, Jan. 2019, doi: 10.1016/j.energy.2018.10.087.

[13] B. Xu *et al.*, "Economic dispatch of micro-grid based on sequential quadratic programming-model and formulation," in *E3S Web of Conferences*, 2019, vol. 136, doi: 10.1051/e3sconf/201913601010.

[14] A. Hoke, A. Brissette, S. Chandler, A. Pratt, and D. Maksimović, "Look-ahead economic dispatch of microgrids with energy storage, using linear programming," in *2013 1st IEEE conference on technologies for sustainability (SusTech)*, 2013, pp. 154–161, doi: 10.1109/SusTech.2013.6617313.

[15] Z. Younes, I. Alhamrouni, S. Mekhilef, and M. Reyasudin, "A memory-based gravitational search algorithm for solving economic dispatch problem in micro-grid," *Ain Shams Engineering Journal*, vol. 12, no. 2, pp. 1985–1994, Jun. 2021, doi: 10.1016/j.asej.2020.10.021.

[16] S. Deb, D. S. Abdelminaam, M. Said, and E. H. Houssein, "Recent methodology-based gradient-based optimizer for economic load dispatch problem," *IEEE Access*, vol. 9, pp. 44322–44338, 2021, doi: 10.1109/ACCESS.2021.3066329.

[17] M. Basu, "Squirrel search algorithm for multi-region combined heat and power economic dispatch incorporating renewable energy sources," *Energy*, vol. 182, pp. 296–305, Sep. 2019, doi: 10.1016/j.energy.2019.06.087.

[18] A. Srivastava and D. K. Das, "A new Kho-Kho optimization algorithm: An application to solve combined emission economic dispatch and combined heat and power economic dispatch problem," *Engineering Applications of Artificial Intelligence*, vol. 94, 2020, doi: 10.1016/j.engappai.2020.103763.

[19] M. A. Mellal and E. J. Williams, "Cuckoo optimization algorithm with penalty function and binary approach for combined heat and power economic dispatch problem," *Energy Reports*, vol. 6, pp. 2720–2723, Nov. 2020, doi: 10.1016/j.egyr.2020.10.004.

[20] Y. Yang, H. Chen, A. A. Heidari, and A. H. Gandomi, "Hunger games search: visions, conception, implementation, deep analysis, perspectives, and towards performance shifts," *Expert Systems with Applications*, vol. 177, Sep. 2021, doi: 10.1016/j.eswa.2021.114864.

[21] H. Saadat, *Power system analysis*, vol. 2. McGraw-hill, 1999.

[22] S. K. Dewangan, A. Jain, and A. P. Huddar, "Comparison of particle swarm optimization with lambda iteration method to solve the economic load dispatch problem," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 4, no. 4, pp. 1900–1907, 2010, doi: 10.15662/ijareeie.2015.0404009.

[23] A. Sheta, H. Faris, M. Braik, and S. Mirjalili, "Nature-inspired metaheuristics search algorithms for solving the economic load dispatch problem of power system: a comparison study," in *Applied nature-inspired computing: algorithms and case studies*, Springer, 2020, pp. 199–230.

[24] W. Aribowo, "Comparison study on economic load dispatch using metaheuristic algorithm," *Gazi University Journal of Sciences*, 2021, doi: 10.35378/gujs.820805.

[25] R. Rahmani, M. F. Othman, R. Yusof, and M. Khalid, "Solving economic dispatch problem using particle swarm optimization by an evolutionary technique for initializing particles," *Journal of Theoretical and Applied Information Technology*, vol. 46, no. 2, pp. 526–536, 2012.

BIOGRAPHIES OF AUTHORS

Widi Aribowo is a lecturer in the Department of Electrical Engineering, Universitas Negeri Surabaya, Indonesia. He is B.Sc in Power Engineering/Sepuluh Nopember Institute of Technology (ITS)-Surabaya in 2005. He is M.Eng in Power Engineering/Sepuluh Nopember Institute of Technology (ITS)-Surabaya in 2009. He is mainly research in the power system and control. He can be contacted at email: widiaribowo@unesa.ac.id.

Supari Muslim is a lecturer in the Department of Electrical Engineering, Universitas Negeri Surabaya, Indonesia. He completed Bachelor of Electronic Engineering Education in Universitas Negeri Surabaya-Surabaya in 1979. He was completed Doctor in Universitas Negeri Yogyakarta – Malang in 1995. His research interests including power system and motor. He can be contacted at email: supari@unesa.ac.id.

Bambang Suprianto is a lecturer in the Department of Electrical Engineering, Universitas Negeri Surabaya, Indonesia. He completed Bachelor of Electronic Engineering Education in Universitas Negeri Surabaya-Surabaya in 1986. He holds Master Engineering in Sepuluh Nopember Institute of Technology (ITS) – Surabaya in 2001. He was completed Doctor of Electrical Engineering in Sepuluh Nopember Institute of Technology (ITS) – Surabaya in 2012. His research interests including power system, control and electronic. He can be contacted at email: bambangsuprianto@unesa.ac.id.