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RESEARCH ARTICLE

Heuristic Algorithms on Economic Dispatch of Multi-Microgrids with Photovoltaics

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ABSTRACT

In this study, an application for economic load dispatch of multi-microgrid systems has been solved by meta-heuristic methods such as particle swarm optimization and genetic algorithm. The solution to the economic dispatch problem should both provide the optimum cost schedule and satisfy the power system constraints. Multi-microgrid system in this study consists of four fuel-based power generation units and two microgrids with photovoltaic panels as renewable energy sources. Simulations were carried out in two case studies, with and without microgrids. While both proposed methods gave better results than the literature study, the best solution was presented by particle swarm optimization with $106583.7/day and $108395.3/day for the systems with and without microgrids, respectively. The simulation results show that both algorithms achieve optimum and reliable results. Multi-microgrids with renewable energy resources increase system reliability and power quality and decrease emissions, transmission losses, and operating costs.

Index terms—Economic load dispatch, genetic algorithm, multi-microgrids, particle swarm optimization, photovoltaics.

I. INTRODUCTION

Depending on the increasing population and developing technology, energy consumption is increasing steadily. Since large-scale power plants generally use fossil fuels, increasing energy consumption over the years has led to a significant decrease in fossil fuel reserves. In addition, concerns based on the increase in carbon emissions have made the renewable energy demand more important. In this case, distributed generation (DG) technology has significant importance and it allows the grid to take full advantage of renewable energy sources (RESs) [1, 2]. Renewable energy sources also reduce emissions, improve power quality, and have high reliability and high efficiency in resource access [1-3].

Since traditional power plants are far from residential and industrial areas, huge power losses occur during energy transmission. Connecting the microgrids (MGs) to the distribution system or operating in an islanded mode eliminates this disadvantage. The aforementioned MGs include DGs which are small-scale power generation units such as photovoltaic panels (PVs) and wind turbines [4-6].

Increasing energy demand increases the orientation toward RESs and gives more importance to economic load dispatch (ELD). The ELD problem (ELDP) basically aims to minimize the costs and has to meet the constraints of the system. The first of these constraints is to meet the demand. The second is that the generation power should be within the generator capacity limits [7].

There are many optimization methods to solve the ELDP. In addition to the classical optimization techniques, meta-heuristic methods are also used to solve these problems. Particle swarm optimization (PSO) and genetic algorithm (GA) are the most preferred meta-heuristic methods. Heuristic methods gain importance due to their advantages such as convenience in solving complex problems and short solution time.

Generic algorithm [1] and PSO [3] were used to ensure ELD of distribution system with two MGs. Authors in [5] proposed the corresponding dynamic programming to ELD of MGs with a battery energy storage system. In [8], various types of ELDP were examined using PSO and classical evolutionary programming. Particle swarm optimization was proposed to ELD considering non-linear generator constraints [9]. Authors in [10] proposed that GA and PSO solve dynamic ELD with valve point effect. In [8], the decomposition and calculation model of the multi-MG (MMG) system was created and the ELDP

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was solved with the differential evolution method considering the transmission losses. The authors in [9] formulated the ELDP for MG and solved it using four methods such as lambda iteration, PSO, direct search method, and lambda logic. Authors in [10] proposed an advanced analytical target cascading theory-based decentralized autonomous dispatching model for an active distribution system with MMGs.

This study examines the ELDP of the MMG system. Multi-microgrid system has four fuel-based generators and two MGs containing PV. The PSO and GA algorithms are developed in matrix laboratory (MATLAB) to solve ELDP for both systems with and without MGs with PV.

The rest of this study is arranged as follows. In section II, the mathematical expression of the ELDP is introduced. In section III, definitions, implementation steps, and parameter settings of the proposed algorithms are given. In section IV, the application and simulation results are presented. Finally, the conclusion part is provided in section V.

II. PROBLEM FORMULATION

A. Objective Function

Economic load dispatch operation minimizes the total operating cost of the system [6]. The total generation cost of generators and MGs can be expressed in (1) and (2), respectively.

$$F_G = \sum_{i=1}^{N} \left(a_i P_i^2 + b_i P_i + c_i \right) \tag{1}$$

$$F_{MG} = \sum_{j=1}^{n} \delta_j \left(P_{MGj} \right) \tag{2}$$

where F_G is the total generation cost of generators [\$/h]; P_i is the real power output of ith generation unit [MW]; a_i, b_i, and c_i are the fuel cost coefficients of the ith generation unit [\$/(MW)^{2}h, \$MW/h, \$/h]; N is the number of generation units of the system; F_{MG} is generation cost of MGs [\$/h]; δ_j is selling or buying price of jth MG [\$]; P_{MGj} is the real power output of jth MG [MW]; n is the number of MGs.

If P_{MGj} has positive value, the jth MG supplies real power to the grid and that means δ_j is the selling price of MG_j. If P_{MGj} has negative value, the jth MG gets real power from the grid and that means δ_j is the buying price of MGj [1].

The total generation cost of the MMG system (F_{MMG} [\$/h]) is the sum of the costs of generators and MGs and it can be expressed as follows:

$$F_{MMG} = F_G + F_{MG} \tag{3}$$

B. Problem Constraints

The power balance of the power system is a major constraint and it can be expressed as follows:

$$P_D = \sum_{i=1}^{N} P_{Gi} + \sum_{j=1}^{n} P_{MGj} \tag{4}$$

where P_D is total load demand [MW].

Each generator and also MG have generation limits and their power output should be within these limits. The capacity constraints of generators and MGs can be expressed as follows:

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \tag{5}$$

$$P_{MGj}^{min} \le P_{MGj} \le P_{MGj}^{max} \tag{6}$$

where P_{Gi}^{min} and P_{Gi}^{max} are the lower and upper limits of the ith generation unit [MW] and P_{MGj}^{min} and P_{MGj}^{max} are the lower and upper limits of the jth MG [MW].

C. Characteristics of MGs

Microgrids can be both consumer and producer. The power outputs of MGs are variable and unstable due to the uncertainties of RES. Therefore, the power output of MGs can be in both negative and positive values. A positive value means that it operates as an energy generation source, and a negative value means that it operates as a load.

Microgrids have controllable and uncontrollable power output, and both must be considered in ELDP. Equations (7) and (8) indicate the minimum and maximum power outputs of MGs.

$$P_{MGj}^{max} = \sum_{i=1}^{N} P_{Sj}^{max} + \sum_{i=1}^{n_{us}} P_{usj} - P_{dj} \tag{7}$$

$$P_{MGj}^{min} = \sum_{i=1}^{N} P_{Sj}^{min} + \sum_{i=1}^{n_{us}} P_{usj} - P_{dj} \tag{8}$$

Main Points

- Proposed heuristic methods, such as genetic algorithm (GA) and particle swarm optimization (PSO), have been used in the application of economic dispatch problem to both systems, with and without microgrids (MGs).
- Proposed heuristic methods obtained more economical results for MMGs systems, especially with PSO.
- Proposed heuristic methods provided an environmental contribution by reducing carbon emissions, as well as technical contributions such as reducing transmission losses and fuel costs by using renewable energy-based MGs.
- Proposed heuristic methods validated the robustness and effectiveness of proposed algorithms by the literature comparison.
- As future work, the dependency on fuel-based generators can be reduced and the reliability of the system can be increased by adding a storage system or different renewable energy sources.

where P_{MGj}^{max} : maximum power output of MGs [MW]; P_{Sj}^{max} : maximum power output of controllable DGs [MW]; P_{usj} : forecast power output of uncontrollable DGs [MW]; P_{dj} : the load of MGs [MW]; P_{MGj}^{min} : minimum power output of MGs [MW]; P_{Sj}^{min} : minimum power output of controllable DGs [MW].

III. OVERVIEW OF THE PROPOSED METHODS

A. Particle Swarm Optimization

The PSO algorithm inspired by the social behavior of bird and fish packs is a population-based heuristic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995 [11]. It is developed for solving non-linear problems and is used to find solutions to multi-parameter and multivariate optimization problems [12]. Individuals in the bird or fish herd have a simple behavior of reaching the food by following the movements of the herd, and this movement can be mathematically defined as the discovery of optimal areas in a search space [13]. Based on this simple behavior, in the PSO algorithm, individuals in the swarm are identified as particles and are released at random positions in the search area. Particles tend to change positions, influenced by the successful movements of other members of the swarm. By reason of this interaction, PSO exhibits a symbiotic behavior feature. As a result of this social behavior, particles present a random movement toward previously found optimal results in the search space [14].

In PSO algorithm, a swarm of particles is assumed to move in a search space to minimize the problem's objective function [15]. Each particle is defined by its position and velocity vectors [3]. x_i describes the current position of the particle and v_i describes the current velocity of the particle. These two vectors for each iteration are defined in (9) and (10). In every iteration, position and velocity vectors are updated according to two parameters. One of these parameters is the best solution that a particle has received so far and it is called p_{besti}. The other one is the particle value that gives the best solution obtained by all particles so far in the entire population and it is called g_{besti}. Each particle's velocity and position vectors are

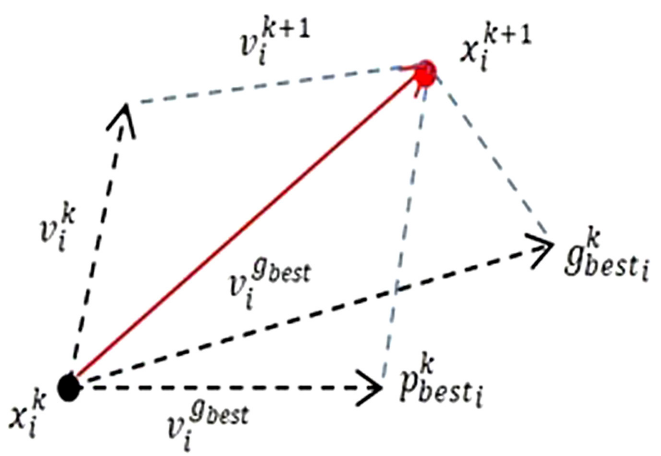

Fig. 1. The vectoral path of each particles [3].

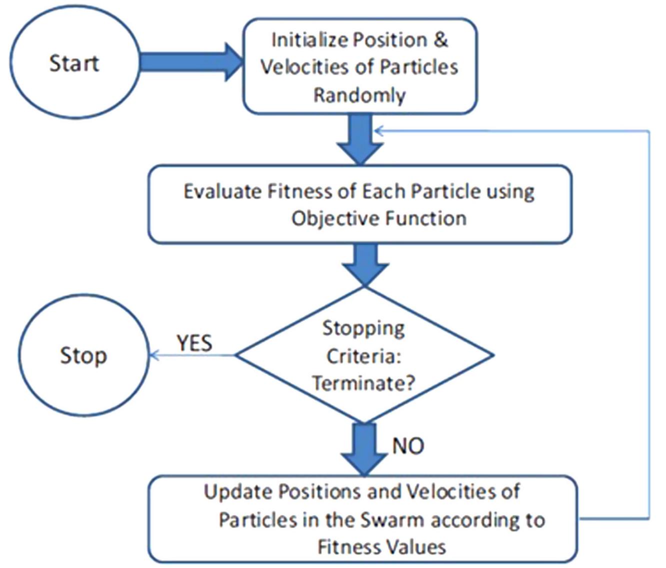

Fig. 2. Flowchart of PSO [16]. PSO, particle swarm optimization.

updated according to (11) and (12). The vectoral path followed by each particle is illustrated in Fig. 1.

$$x_i^k = \left[x_{i1}, x_{i2}, \ldots, x_{iD}\right] \tag{9}$$

$$v_i^k = \left[v_{i1}, v_{i2}, \ldots, v_{iD}\right] \tag{10}$$

$$v_i^{k+1} = wv_i^k + c_1 r_1 \left(p_{best\,i}^k - x_i^k\right) + c_2 r_2 \left(g_{best\,i}^k - x_i^k\right) \tag{11}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{12}$$

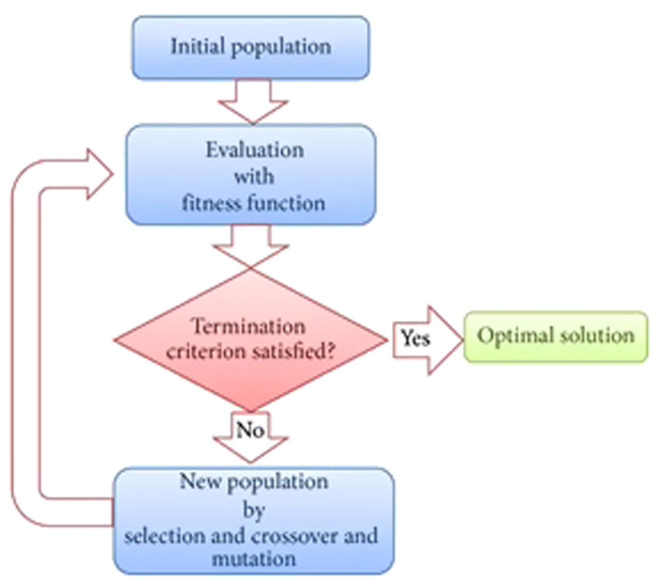

Fig. 3. Flowchart of GA [23]. GA, generic algorithm.

where v_i^{k+1} : velocity of *i*th particle in (*k*+1)th iteration; v_i^k : velocity of *i*th particle in *k*th iteration;*W*: inertia weight;C_1, C_2: acceleration constant;r_1, r_1: uniform random value; $p_{best\,i}^k$: *i*th particle's best solution in *k*th iteration; $g_{best\,i}^k$: best solution of all particles in *k*th iteration; x_i^k : position of *i*th particle in *k*th iteration; x_i^{k+1} : position of *i*th particle in (*k*+1)th iteration.

Acceleration constants are usually chosen as equal and 2 but [0, 4] is the general range for this quantity [12, 16]. The inertia weight can be defined as follows:

$$w(k) = w_{max} - \left(\frac{w_{max} - w_{min}}{K} \right) \times k \tag{13}$$

where W_{max} is maximum inertia weight; W_{min} is minimum inertia weight; *K* is the number of iterations; *K* is the current iteration number.

The standard flowchart of PSO is shown in Fig. 2 [16].

B. Genetic Algorithm

The GA is an iterative evolution-based algorithm that searches for the best solution in a complex multi-dimensional search space according to the survival of the fittest principle. Generic algorith which is inspired by Darwin's evolution theory was developed by John Holland in 1975 [17, 18]. In GA, the birth, reproduction, and extinction of individuals by natural selection are simulated [19].

Genetic algorithm creates a solution set consisting of independent solutions, each of which is a vector on a multidimensional space. In this way, the probability of reaching a solution by evaluating a single point increases [20, 21]. Besides, it has an advantage with the variety of solutions it provides and its application to multivariate problems [21].

The GA modifies the population iteratively. In each iteration, new individuals are created by randomly selecting individuals and a new generation emerges. This process continues until the maximum number of iterations is reached and the optimum result is obtained. Firstly, for the implementation of algorithm, a random population is created. Each individual in a population is called as a chromosome. Each chromosome in a population represents possible solution and has a fitness value [22]. This value was calculated for each individual with the fitness function. The chromosome with the best fitness value gives the most optimal result. Equation (1) indicates the fitness function.

$$F(x) = \frac{1}{1 + f(x)} \tag{14}$$

where *F*(*x*) is fitness function and *f*(*x*) is the cost function. *F*(*x*) ranges from 0 to 1. As *F*(*x*) gets closer to 1, the probability of an individual being transferred to the next generation increases [17, 18].

After the population is created, a new population is produced from this population by means of genetic operators. These genetic operators are selection, crossover, and mutation:

Selection: Roulette wheel technique is generally used for this process. Selection is made according to the fitness values of the individuals. The selected individuals are called parents.

Crossover: New individuals are created from the selected parents via the crossover operator. The crossover rate is considered when considering this process.

Mutation: After the crossover operation, new individuals are randomly mutated. The mutation rate is considered when considering this process.

The schematic flowchart of GA is given in Fig. 3 [23].

C. Implementation of the Proposed Algorithms on ELDP

Implementation steps of PSO on ELDP are given as follows [24]:

Step 1: PSO parameters (number of particles, iteration number, W_{min}, W_{max}, C_1, C_2) and system data (P_{Gi}^{min} , P_{Gi}^{max} , a_i, b_i, c_i, P_D) are defined.

TABLE I.
PSO PARAMETERS

PSO Parameter	Value
Number of particles	50
Maximum iteration	50
Acceleration constants: C_1=C_2	2
Inertia weights: W_{min} & W_{max}	0.1 and 0.9

PSO, particle swarm optimization.

TABLE II.
GA PARAMETERS

Parameter	Value
Population size	50
Maximum iteration	50
Crossover rate	0.8
Mutation rate	0.1

GA, generic algorithm.

TABLE III.
GENERATOR PARAMETERS

Parameters	G1	G2	G3	G5
a_i	0.168	0.168	0.505	0.674
b_i	21.05	16.8	12.63	27.39
c_i	40	40	30	30
P_{Gi}^{min}	20	10	10	10
P_{Gi}^{max}	80	55	55	55

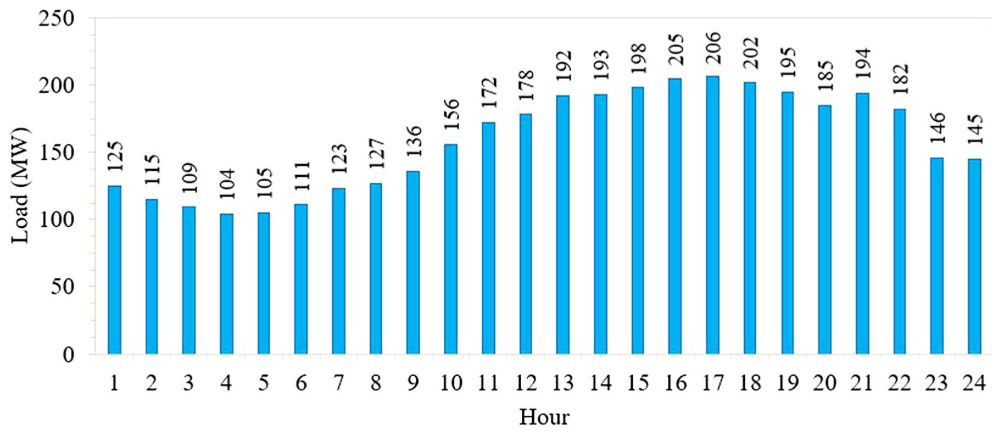

Fig. 4. Daily load.

Step 2: Particles of the swarm are generated randomly by using (15):

$$P_i = P_i^{min} + rand \times \left(P_i^{max} - P_i^{min}\right) \quad (15)$$

where P_i is the power output [MW] and P_i^{min} and P_i^{max} are generation limits [MW]

Step 3: It is evaluated whether the generation power meets the demand and whether it is within the generation limits. When the number of particles that meet these constraints reaches the desired number, the next step is started.

Step 4: p_{besti} and g_{besti} are determined.

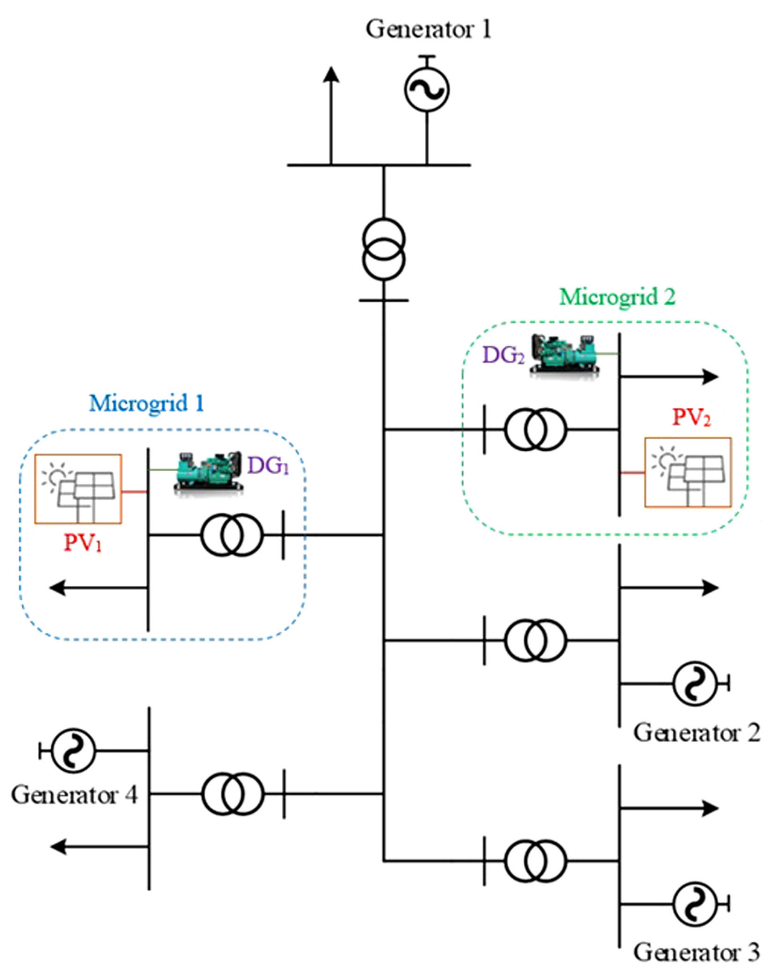

Fig. 5. Single-line diagram of the system.

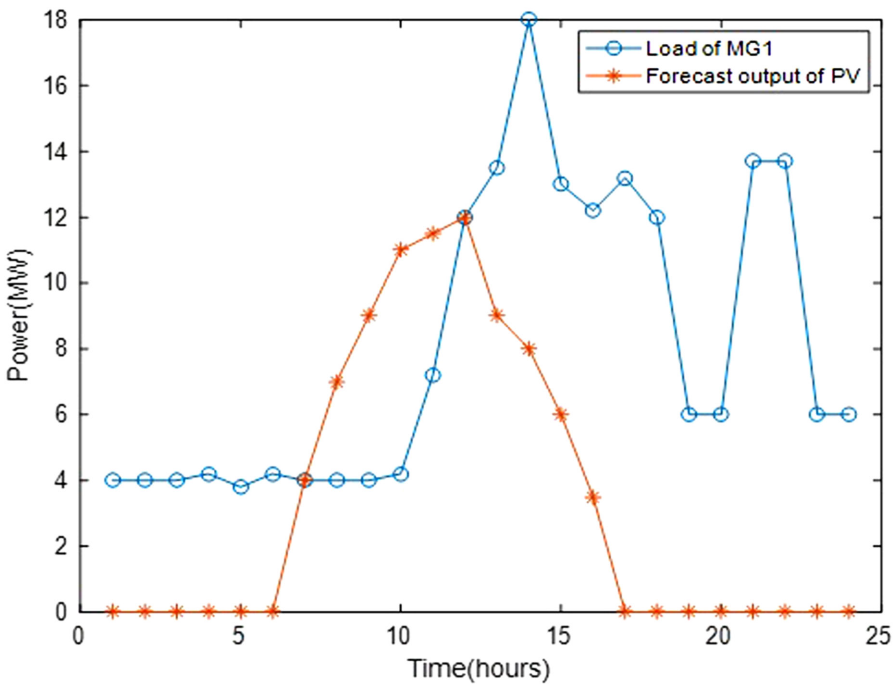

Fig. 6. Forecast PV power output and daily load of MG1 [1]. PV, photovoltaic; MG1, microgrid1.

Step 5: The iteration is started and the inertia weight is calculated according to (13). In each iteration, velocity and positions of particles are updated according to (11) and (12).

Step 6: p_{besti} and g_{besti} are updated.

Step 7: When the maximum number of iterations is reached, the algorithm is stopped and the optimum solution results are obtained.

Implementation steps of GA on ELDP are given as follows:

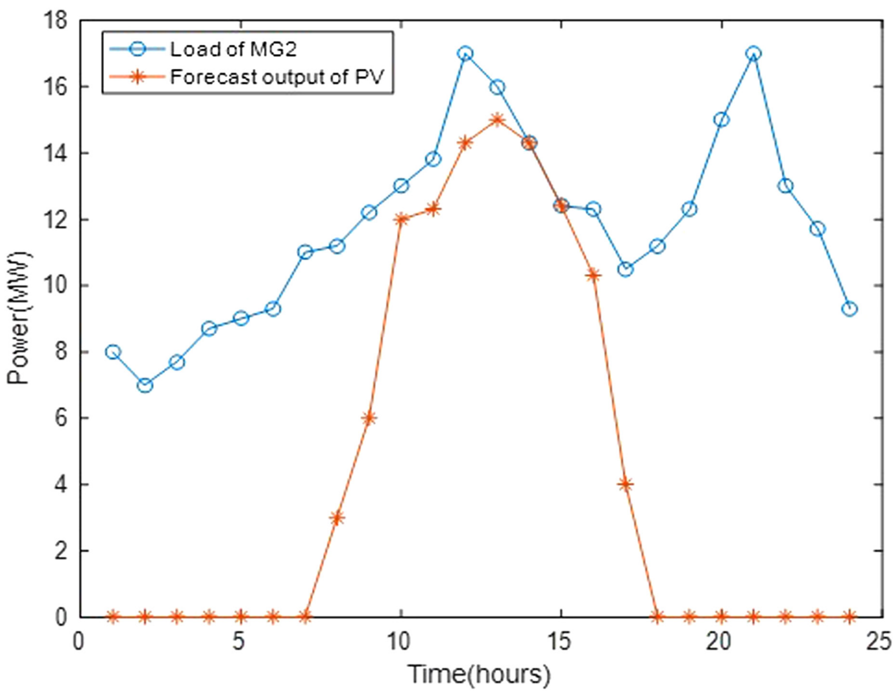

Fig. 7. Forecast PV power output and daily load of MG2 [1]. PV, photovoltaic; MG2, microgrid2.

TABLE IV.
POWER DISPATCH FOR THE SYSTEMS WITH MGS AND WITHOUT MG BY USING PSO

	Power System Without MG				Power System With MGs					
Hour	G1 [MW]	G2 [MW]	G3 [MW]	G4 [MW]	G1 [MW]	G2 [MW]	G3 [MW]	G4 [MW]	MG1 [MW]	MG2 [MW]
1	31.30	43.95	18.75	30.99	29.73	42.38	18.23	27.06	5.3	2.3
2	29.23	41.88	18.06	25.82	29.23	41.88	18.06	25.82	1	-1
3	27.99	40.63	17.65	22.72	28.63	41.28	17.86	24.33	-1.8	-1.3
4	26.95	39.60	17.30	20.14	27.94	40.59	17.63	22.62	-1.4	-3.4
5	27.16	39.81	17.37	20.66	28.21	40.86	17.72	23.29	-0.6	-4.5
6	28.40	41.05	17.78	23.76	28.92	41.57	17.96	25.05	2.5	-5
7	30.89	43.54	18.61	29.96	29.66	42.31	18.21	26.91	5.9	0
8	31.72	44.36	18.89	32.02	27.28	39.93	17.41	20.97	15.5	5
9	33.58	46.23	19.51	36.67	28.69	41.34	17.88	24.48	16.3	7.3
10	37.73	50.37	20.89	47	31.38	44.03	18.78	31.20	14.5	16.1
11	41.16	53.81	22.03	55	34.29	46.93	19.74	38.43	15.6	17
12	44.76	55	23.23	55	35.96	48.61	20.30	42.61	14.8	15.7
13	55.27	55	26.72	55	40.34	52.99	21.76	53.51	6.9	16.5
14	56.02	55	26.97	55	41.29	53.93	22.07	55	0.7	20
15	59.77	55	28.22	55	47.69	55	24.20	55	3.8	12.3
16	65.02	55	29.97	55	50.77	55	25.22	55	2.3	16.7
17	65.77	55	30.22	55	62.62	55	29.17	55	0	4.2
18	62.77	55	29.22	55	55.19	55	26.70	55	2.4	7.7
19	57.52	55	27.47	55	51.07	55	25.32	55	2.7	5.9
20	50.01	55	24.98	55	42.81	55	22.58	55	4.2	5.4
21	56.77	55	27.22	55	59.47	55	28.12	55	-1.8	-1.8
22	47.76	55	24.23	55	47.84	55	24.25	55	-1.8	1.7
23	35.65	48.30	20.20	41.84	36.32	48.97	20.42	43.49	-1	-2.2
24	35.45	48.09	20.13	41.32	32.59	45.24	19.18	34.19	6	7.8

PSO, particle swarm optimization; MG, microgrid.

Step 1: GA parameters (population size, crossover rate, mutation rate, iteration number) and system data (P_{Gi}^{min} , P_{Gi}^{max} , a_i, b_i, c_i, P_D) are defined.

Step 2: Chromosomes are randomly generated by using (15).

Step 3: When the number of chromosomes satisfying the system constraints is reached, the fitness value for each chromosome is calculated using (14).

Step 4: The roulette wheel selection is applied and the parents are selected randomly.

Step 5: Crossover and mutation operations are applied.

Step 6: The fitness value is calculated for the chromosomes in the new generation and the next iteration is passed.

Step 7: When the stopping criteria (max. iteration number) is met, the algorithm is stopped and the optimum results are obtained.

D. Parameter Settings

Partilce swarm optimization and GA parameters used in this study to optimize ELD problem are given in Table 1 and Table 2, respectively.

TABLE V.
POWER DISPATCH FOR THE SYSTEMS WITH MGS AND WITHOUT MG BY USING GA

	Power System Without MG				Power System With MGs					
Hour	G1 [MW]	G2 [MW]	G3 [MW]	G4 [MW]	G1 [MW]	G2 [MW]	G3 [MW]	G4 [MW]	MG1 [MW]	MG2 [MW]
1	31.35	43.77	18.77	31.12	29.78	42.20	18.24	27.19	5.3	2.3
2	29.28	41.70	18.08	25.94	29.28	41.70	18.08	25.94	1	-1
3	28.03	40.47	17.66	22.84	28.68	41.11	17.88	24.45	-1.8	-1.3
4	26.99	39.43	17.32	20.26	27.99	40.43	17.65	22.74	-1.4	-3.4
5	27.20	39.64	17.39	20.77	28.26	40.69	17.74	23.41	-0.6	-4.5
6	28.45	40.88	17.80	23.88	28.97	41.39	17.97	25.17	2.5	-5
7	30.94	43.35	18.63	30.08	29.71	42.14	18.22	27.03	5.9	0
8	31.77	44.18	18.91	32.15	27.33	39.76	17.43	21.09	15,5	5,9
9	33.64	46.04	19.53	36.81	28.74	41.17	17.90	24.60	16.3	7.3
10	37.78	50.16	20.91	47.15	31.44	43.85	18.79	31.32	14.5	16.1
11	41.29	53.65	22.07	55	34.34	46.74	19.76	38.56	15.6	17
12	44.78	55	23.23	55	36.02	48.41	20.32	42.75	14.8	15.7
13	55.27	55	26.72	55	40.40	52.76	21.78	53.66	6.9	16.5
14	56.02	55	26.97	55	41.41	53.77	22.11	55	0.7	20
15	59.78	55	28.22	55	47.70	55	24.21	55	3.8	12.3
16	65.03	55	29.97	55	50.77	55	25.23	55	2.3	16.7
17	65.78	55	30.22	55	62.63	55	29.17	55	0	4.2
18	62.78	55	29.22	55	55.20	55	26.70	55	2.4	7.7
19	57.53	55	27.47	55	51.07	55	25.33	55	2.7	5.9
20	50.03	55	24.98	55	42.82	55	22.58	55	4.2	5.4
21	56.78	55	27.22	55	59.48	55	28.12	55	-1.8	-1.8
22	47.77	55	24.23	55	47.85	55	24.26	55	-1.8	1.7
23	35.71	48.10	20.22	41.97	36.37	48.76	20.44	43.63	-1	-2.2
24	35.50	47.89	20.15	41.45	32.64	45.05	19.19	34.32	6	7.8

MG, microgrid; GA, generic algorithm.

IV. SIMULATION RESULTS AND DISCUSSION

The MMG system used in this study consists of two MGs including RESs and four fuel-based units of generator sets. Generator parameters and daily load profile of the system are given in Table 3 and Fig. 4, respectively [1]. The single-line diagram of the MMG system is given in Fig. 5.

As the MG1 and MG2 are solar-based DGs, their power output is not indefinite. Therefore, just like in local daily load, power outputs should be estimated according to historical and environmental factors. Since the MGs contain PVs, MG1 provides power to the system in periods 6.00–17.00 and MG2 in periods 7.00–18.00.

The controllable DG power output capacity of MG1 is 12 MW, while the output capacity of MG2 is 20 MW. The forecast PV power output and daily local load curve for MG1 and MG2 are given in Fig. 6 and Fig. 7, respectively.

Microgrids should primarily meet local load. If the generation power of the MG cannot meet their local load, the lack of power amount is supplied from the system. If the MG generates more power than its local load, excess power is supplied to the system. Microgrid1's selling price is \$27/MW and MG2's selling price is \$28/MW. Likewise, the buying price of both MGs is equal to \$22/MW.

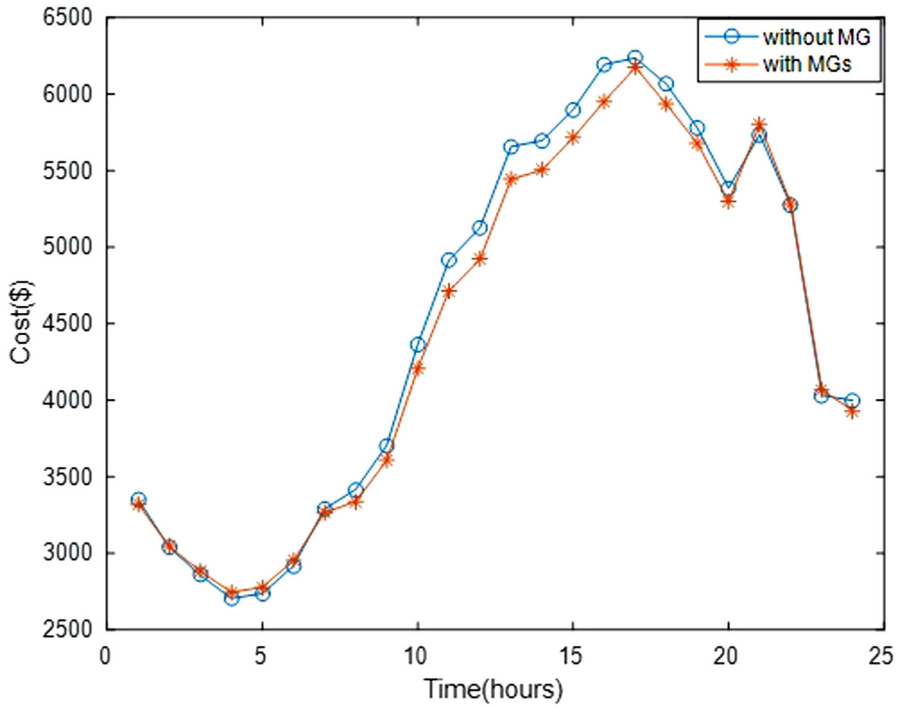

Fig. 8. Optimal costs in 24 hours by PSO. PSO, particle swarm optimization.

Tables 4 and 5 show the economic dispatch results of the system with and without MGs by PSO and GA, respectively. Hourly optimal costs of the system both with and without MGs are illustrated graphically in Fig. 8 for PSO and Fig. 9 for GA. The total costs have been obtained as \$108395.3/day in the system without MG and as \$106583.7/day in the system with MGs by PSO and \$108456.6/day and \$106642.9/day by GA. It is clearly seen that MMG-containing RES provides economic benefits.

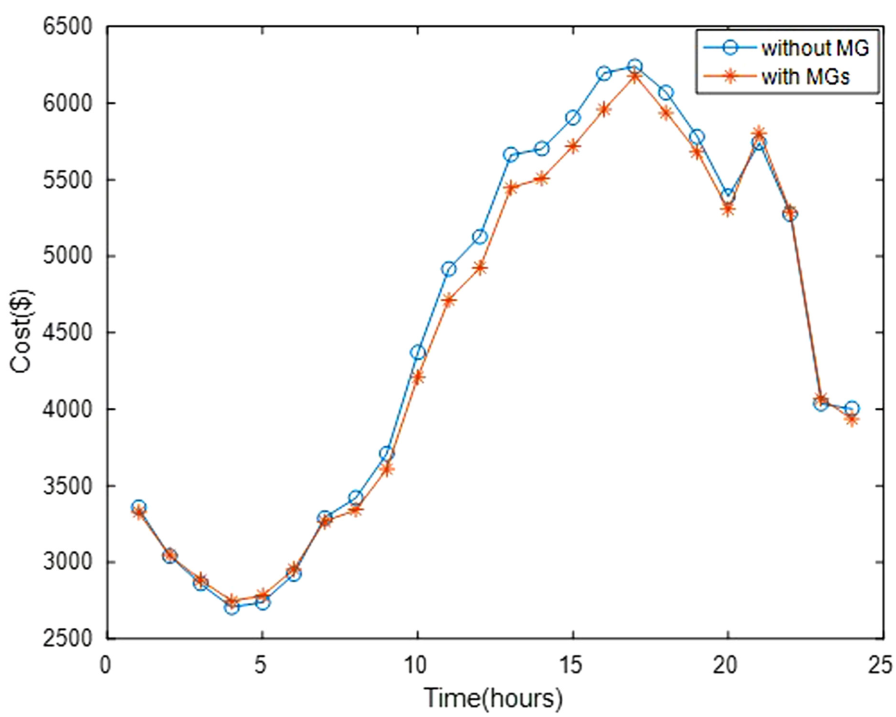

Fig. 9. Optimal costs in 24 hours by GA. GA, generic algorithm.

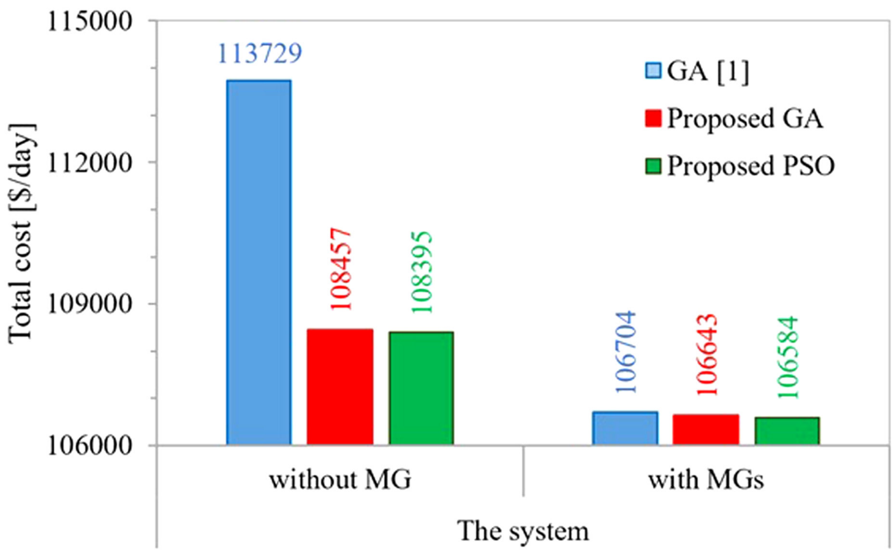

Fig. 10. Comparison of the proposed GA and PSO with the GA [1] in the literature. PSO, particle swarm optimization; GA, generic algorithm.

It is seen clearly from the comparison of Fig. 8 and Fig. 9 that the inclusion of MGs resulted in a reduction in cost. From 12:00 to 18:00 hours, when is the most efficient interval of PVs, the total cost difference between with MGs and without MGs is the greatest. Even if in the night time, the difference is great. The reason is that the MGs are insufficient to meet local loads during these hours, so power should be purchased from the system. It is normal for this difference to occur when the purchase cost is considered.

The comparison of the proposed algorithms in this study and GA in [1] is shown in Fig. 10.

VI. CONCLUSIONS

The inclusion of MGs including RES in distribution systems is one of the most effective factors in the near future. Renewable energy-based MGs increase power quality and efficiency while reducing transmission line losses and carbon emissions.

In this study, the ELDP of an MMG system with two MGs including PV and four fuel-based generators is approached by using PSO and GA algorithms, and the total fuel cost is calculated as $106583.7/day and $106642.9/day, respectively. When MGs are neglected, the total cost is calculated as $108395.3/day for PSO method and $108456.6/day for GA. The inclusion of MGs including RES resulted in a cost reduction of approximately $1800/day. Optimal, reliable, and close results were obtained in both methods. Also, these results are better than the study in the literature. Since GA algorithm has more complex structure in practice, its calculation process is longer than that of PSO.

Multi-microgrid systems including PV provided a significant reduction in total operation cost. Besides the other advantages, MMG system with PV reduces the load dispatching on the fuel-based generators and provides a significant reduction in fuel costs and emissions.

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REFERENCES

1. Z. Qiongyao, L. Shirong, Z. Ying, C. Xueting, and Z. Lingwei, “Economic dispatch of distribution network with multi-microgrid,” in 2015 34th Chinese Control Conference (CCC), 2015, pp. 9060–9065.
2. G. Liao, “The optimal economic dispatch of smart microgrid including Distributed Generation,” in International Symposium on Next-Generation Electronics, 2013, pp. 473–477.
3. U. Firdaus, and O. Penangsang, “Economic dispatch of multi microgrid systems with renewable energy sources using particle swarm optimization,” in International Seminar on Intelligent Technology and Its Applications (ISITIA), 2016, pp. 595–600.
4. J. Zhu, *Optimization of Power System Operation*. Hoboken, NJ, USA: John Wiley & Sons, Inc, 2015.
5. L. Xiaoping, D. Ming, H. Jianghong, H. Pingping, and P. Yali, “Dynamic economic dispatch for microgrids including battery energy storage,” in The 2nd International Symposium on Power Electronics for Distributed Generation Systems, 2010, pp. 914–917.
6. P. Li, X. Guan, J. Wu, and D. Wang, “An integrated energy exchange scheduling and pricing strategy for multi-microgrid system,” in IEEE International Conference of IEEE Region 10 (TENCON 2013), 2013, pp. 1–5.
7. A. J. Wood, and B. F. Wollenberg, *Power Generation Operation and Control*. New York, USA: John and Sons, 1996.
8. X. Li, Y. Zeng, and Z. Lu, “Decomposition and coordination calculation of economic dispatch for active distribution network with multi-microgrids,” *Int. J. Electr. Power Energy Syst.*, vol. 135, p. 107617, 2022. [CrossRef]
9. A. Maulik, and D. Das, “Optimal operation of microgrid using four different optimization techniques,” *Sustain. Energy Technol. Assess.*, vol. 21, pp. 100–120, 2017. [CrossRef]

10. M. Xie, X. Ji, X. Hu, P. Cheng, Y. Du, and M. Liu, "Autonomous optimized economic dispatch of active distribution system with multi-microgrids," *Energy*, vol. 153, pp. 479–489, 2018. [CrossRef]
11. R. Eberhart, and J. Kennedy, "A new optimizer using particle swarm theory," in MHS, Proceedings of the Sixth International Symposium on Micro Machine and Human Science, 1995, pp. 39–43.
12. S. Tamer, and C. Karakuzu, "Parçacık sürüsü optimizasyon algoritması ve Benzetim Örnekleri," in ELECO 2006 Elektrik-Elektronik- Bilgisayar Sempozyumu, 2006, pp. 302–306.
13. J. Kennedy, and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95 - International Conference on Neural Networks*, vol. 4, 1995, pp. 1942–1948.
14. Y. Zeybekoğlu, *Ünite Yüklenme Probleminin Parçacık Sürü Optimizasyon Yöntemi ile Çözümü* [M.Sc. dissertation]. Istanbul, Turkey: Istanbul Technical University, 2011.
15. Z. -L. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints," *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1187–1195, 2003. [CrossRef]
16. K. Gopalakrishnan, "Neural network-swarm intelligence hybrid nonlinear optimization algorithm for pavement moduli back-calculation," *J. Transp. Eng.*, vol. 136, no. 6, pp. 528–536, 2010. [CrossRef]
17. M. Purlu, and B. E. Turkay, "Dynamic economic dispatch with valve point effect by using GA and PSO algorithm," in 6th International Conference on Control Engineering & Information Technology (CEIT), 2018, pp. 1–6.
18. D. E. Goldberg, *Genetic Algorithms in Search, Optimization & Machine Learning*. Reading, United States of America: Addison-Wesley, 1989.
19. T. Murata, and H. Ishibuchi, "Performance evaluation of genetic algorithms for flowshop scheduling problems," in Proceedings of the First IEEE Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence, 1994, pp. 812–817.
20. Ö. P. Arslan, *Güç Sistemlerinin Ekonomik ve Çevresel Ekonomik Yük Dağıtımında Yeni Optimizasyon Tekniklerinin Kullanımı* [M.Sc. dissertation]. Kırıkkale, Turkey: Kırıkkale University, 2015.
21. M. Pürlü, *Üretim Sistemlerinde Valf-Nokta Etkili Konveks Olmayan Dinamik Ekonomik Yük Dağıtımı* [M.Sc. dissertation]. Istanbul, Turkey: Istanbul Technical University, 2017.
22. V, J. S. Kumar, Y. Singh, and S. Sood, "Optimal Economic Load Dispatch Using Genetic Algorithms," *World Acad. Sci. Eng. Technol. Int. J. Electr. Comput. Eng.*, vol. 9, no. 4, pp. 463–470, 2015.
23. S. Li, L. Kang, and X. M. Zhao, "A survey on evolutionary algorithm based hybrid intelligence in bioinformatics," *BioMed Res. Int.*, vol. 2014, p. 362738, 2014. [CrossRef]
24. E. Aydin, M. Purlu, and B. E. Turkay, "Economic dispatch of multi-microgrid systems by using particle swarm optimization," in 13th International Conference on Electrical and Electronics Engineering (ELECO), IEEE Publications, 2021, pp. 268–272.