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Research Article

Resolving Economic Dispatch with Uncertainty Effect in Microgrids Using Hybrid Incremental Particle Swarm Optimization and Deep Learning Method

Nasyith Hananur Rohiem[1], Adi Soeprijanto[1], Dimas Fajar Uman Putra[1], Mat Syai'in[2], Irrine Budi Sulistiawati[3*], Muhammad Zahoor[4], and Luqman Ali Shah[5]

[1]Department of Electrical Engineering, Sepuluh Nopember Institute of Technology (ITS), 1st Campus ITS Keputih, Gedung B, C & AJ, Sukolilo, Surabaya 60111, Indonesia
[2]Department of Marine, Shipbuilding Institute of Polytechnic Surabaya, 1st Campus ITS Keputih, Sukolilo, Jl. Teknik Kimia, Surabaya 60117, Indonesia
[3]Department of Electrical Engineering, National Institute of Technology (ITN) Malang, 2nd Campus ITN, Jl. Raya Karanglo, Malang 65145, Indonesia
[4]Department of Biochemistry, University of Malakand, Lower Dir 18800, Pakistan
[5]National Center of Excellence in Physical Chemistry (NCE), University of Peshawar 25120, Pakistan

Abstract: Microgrids are one example of a low voltage distributed generation pattern that can cover a variety of energy, such as conventional generators and renewable energy. Economic dispatch (ED) is an important function and a key of a power system operation in microgrids. There are several procedures to find the optimum generation. The first step is to find every feasible state (FS) for thermal generator ED. The second step is to find optimum generation based on FS using incremental particle swarm optimization (IPSO), FS is assumed that all units are activated. The third step is to train the input and output of the IPSO into deep learning (DL). And the last step is to compare DL output with IPSO. The microgrids system in this paper considered 10 thermal units and a wind plant with power generation based on probabilistic data. IPSO shows good results by being capable to generate a total generation as the load requirement every hour for 24 h. However, IPSO has a weakness in execution times, from 10 experiments the average IPSO process takes 30 min. DL based on IPSO can make the execution time of its ED function faster with an 11 input and 10 output architecture. From the same experiments with IPSO, DL can produce the same output as IPSO but with a faster execution time. From the total cost side, wind energy is affecting to reduce total cost until USD 22.86 million from IPSO and USD 22.89 million from DL.

Keywords: Conventional Thermal Generator, Economic Dispatch, Low Voltage Distribution, Power System Operation, Probabilistic, Renewable Energy.

1. INTRODUCTION

Microgrids are one example of low voltage distributed generation with a variety of energy sources, such as conventional thermal generators and renewable energy (RE) [1, 2]. RE like a wind turbine (WTs) [3–11] has big uncertainty and produces unstable generation because of nature. With probabilistic data, it can give important information about the RE plant area also information about the power generation produced by WTs [11]. A microgrid has a lower cost of energy supply with less carbon emission because the system can be operated to handle some level load or to support the main grid with a small source [1, 2]. One of the main functions of microgrid generation control is to decide unit commitment (UC) and the economic dispatch (ED) but this research will concern ED [1, 2].

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*Corresponding Author: Irrine Budi Sulistiawati <irrine@lecturer.itn.ac.id>

Economic dispatch (ED) is the key to power system operation to find the optimum generation from every feasible initial of unit combination [6, 9, 12–14]. To find a better feasible solution, a priority list (PL) is a good initializer and has shown promising results [6, 15–18]. Optimum generation from every feasible solution can be defined by some promising method [15–18] such as particle swarm optimization (PSO), genetic algorithm (GA), Lagrange relaxation (LR), etc. hybrid models which are compared one method with another may have a better result than individuals method.

In this manuscript, proposed incremental particle swarm optimization (IPSO) to solve ED in a microgrid system. IPSO is a combination of PSO and ISL (incremental social learning) [19] to improve the performance of PSO and to eliminate local optimal [20–25]. The feasibility state is assumed that all units are activated both before and after WTs are affected. Feasibility state and output generation from IPSO is trained into a DL [26, 27] to speed up the execution time. Not only to speed up the execution time, but DL also to be a promising algorithm to make quickly and precisely decisions maker function with large training data [28–32].

2. MATERIALS AND METHODS

A microgrids system consists of a conventional generator or thermal plant and RE based on the generator [1, 2].

2.1 Generator

The thermal plant in this paper used a 10 unit generator with a 24 h load [1, 2] for the unit generates. For the wind plant, the total capacity installed [1, 2] of wind power is 560 kW from four generators and each capacity is 140 kW. In this manuscript, a detailed model for the simulation of wind power generation is often used in the field.

Wind plant converts from wind speed or kinetic energy to electric energy and equation [1, 2, 4, 5] to convert power from a wind plant is shown in Equation (1).

$$P = 0.5\,\rho\, A\, C_p\ V^3 \tag{1}$$

Where P is power (W), ρ is air density (kg m^{-3}), A is rotor area (m^2), C_p is coefficient power and V^3 is wind speed (m s^{-1}).

In this research-based on wind plant data, equation [1, 2] power output of the wind generator can be presented as shown in Equation (2):

$$P_{out} = aV^4_{\ w} + bV^3_{\ w} + cV^2_{\ w} + dV_w + e \tag{2}$$

Where Pout is power generated (W) and V is wind speed (m s^{-1}).

2.2 Constraint

In this research, ED is determined based on several constraints with the mathematical [1, 2, 6] equations as shown in Equation (3) to Equation (6)

2.2.1 Thermal Cost

$$F_i\,(P_{Ti}\,(t)) = a_i + b_i\,P_{Ti}\,(t) + c_i\,P_{Ti}(t)^2 \tag{3}$$

Where, ai, bi and ci are quadratic cost coefficients, T_i^{down} is minimum downtime (hr), T_i^{up} is minimum uptime (hr), $T_{i,cold}$ is cold start hours (hr), and $T_{i,0}$ is unit first initialize (hr).

2.2.2 Generation Limit

$$P_{i,min}\,X_{i,t}\ \le\ P^s_{\ i,t}\ \le\ P_{i,max}\,X_{i,t} \tag{4}$$

Where, $P_{i,min}$ is minimum power generation (W), $P_{i,t}$ is the output power of unit i at time t (W), $P_{i,max}$ is maximum power generation (W).

2.2.3 Spinning Reserve

$$\sum_{i=1}^{n} \boldsymbol{P_T(t) + P_R(t) \le I_i(t) P_{T_i}^{max}} \tag{5}$$

2.2.4 Net Load

$$Load(t) = Thermal\ load(t) - Wind(t) \tag{6}$$

2.3 Load

The wind speed probability data [23, 24] used is wind data in December 2015 as shown in Figure 1 at an altitude of 50 m above ground in the Sidrap wind plant [24] with a geographical position between 03043′ to 04009 *S* 11 & 119041′ to 120010′*E* or *Long*: 3 980, *Lat* 119 710.

WTs generation [(determined by Equation (2)] as shown in Figure 2 (blue line) is determined based on hourly wind speed probability data on 25 December 2015 and thermal load [1, 2] before WTs is affected as shown in Figure 2 (orange line). Based on Equation (6), the new loads after the wind turbine effect are shown in Figure 2 (grey line).

2.4 Initial State

All states are based on PL defined by FLAC [6] to sort generators from the lowest to the highest. Table 1 is a table of the priority list.

Table 1. PL generator microgrid.

Unit	1	2	3	4	5	6	7	8	9	10

The feasibility state is determined based on the Pmax value which must be greater than the load. The feasibility state in this paper takes into account the spinning reserve by 10 %. Pmax is the sum of the maximum active generator limits. In this section, all units are assumed to be active. If all units are active, the generation limit has a minimum value of 800 kW and a maximum of 3 200 kW as shown in Table 2.

Table 2. Initial unit.

Unit										Limit (kW)	
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Min**	**max**
1	1	1	1	1	1	1	1	1	1	800	3 200

2.5 IPSO based solution method for ED

IPSO used in this paper is developed by Oca et al. [20]. IPSO is combined by ISL [20] to schedule time for adding particles [20, 21] to the population and PSO. For growing the new population from IPSO [25] can be calculated using Equation (7).

$$x'_{new,j} = x'_{new,j} + U\,(p_{mode\ el,j} - x_{\ new,j}) \qquad (7)$$

Where $x'_{new,j}$ new,j is new particle's update position, $x'_{new,j}$ is new particle's original random position, $p_{mode\ el,j}$ is the model particle's position and U is a random number (0–1).

As shown in Figure 3 of the IPSO process, it is the overall process. FLAC data input is used to determine all state PL and the result as shown in Table 3. Then based on the load at a certain hour IPSO determines the feasibility state. There are two cases to determine feasibility state in this paper, before wind turbines, and after WTs are affected. The feasibility state before and after the wind turbine effect is shown the same as Table 4, then the IPSO optimization process starts. The optimal solution to determine the generation value of an active unit based on state conditions that can meet the load supply at certain times in every iteration. The generation value is adjusted to the Pmin and Pmax limits. The objective function from each iteration of the new individual should be compared with another one in the next iteration and the lower cost from the objective function at all iterations is used as local best condition and global best condition after all particles were evaluated.

2.6 Deep Learning (DL) based on IPSO

DL used in this paper is constructed from 11 input describe load then feasibility state and 10 output describe power generation of active generator. DL construction is shown in Figure 4.

DL training input is determined from the load and feasible combination of generators while the data output for DL training is taken from IPSO generation output based on a combination of generators that allow at certain hours. The DL training process uses MATLAB software as shown in Figure 4.

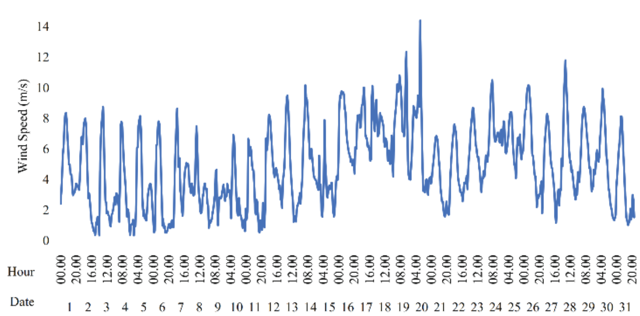

Fig. 1. Wind speed during December 2015.

3. RESULTS AND DISCUSSION

There are several experiments and simulations have been carried out in this study, including ED based on IPSO, ED DL based on IPSO, total cost results, comparison of ED IPSO and ED DL before and after being affected by WTs. For the thermal unit data [1, 2] as shown in Table 5 and wind generator data as shown in Table 6.

Table 6. Plant data of wind generator.

P_r	V_{ci}	V_r	V_{co}	a	b	c	d	e
140	3	15.01	17	-0.02	0.033	-0.9	-2.1	7.1

Where, P_r is rate power (kW), V_{ci} is wind speed cut in (m s^{-1}), Vco is wind speed cut off (m s^{-1}) and V_r is rating speed (m s^{-1}).

3.1 Output generation IPSO

IPSO in this paper construct by a total of 1 500 particles in the last iterations, 1 000 iterations. The incremental function which makes a new population in every iteration of the IPSO process makes this method out from the local optimum and makes the output generation shows good result. Total power generation is equal to load at a certain hour, both before and after the wind turbine effect as shown in Figure 2. Table 4 shows all hours of loading results. All of them are from both cases based on feasibility state.

3.2 Output generation DL

DL in this paper has been trained using 2 700 data based on the output process from IPSO. DL training input as shown in Table 3 and output data in Table 7. Sorted by the smallest to largest load both before and after being affected by WTs. DL

Table 5. Thermal unit data.

Unit	$P_{i,max}$ (kW)	$P_{i,min}$ (kW)	a_i (USD hr^{-1})	b_i (USD kWh^{-1})	c_i (USD kWh^{-2})
1	600	100	5	4	10
2	400	100	5	6	20
3	400	100	20	8	25
4	400	100	20	10	25
5	300	50	30	10	20
6	300	100	30	12	20
7	200	100	40	14	15
8	200	50	40	16	15
9	100	50	55	15	12
10	100	50	55	17	12

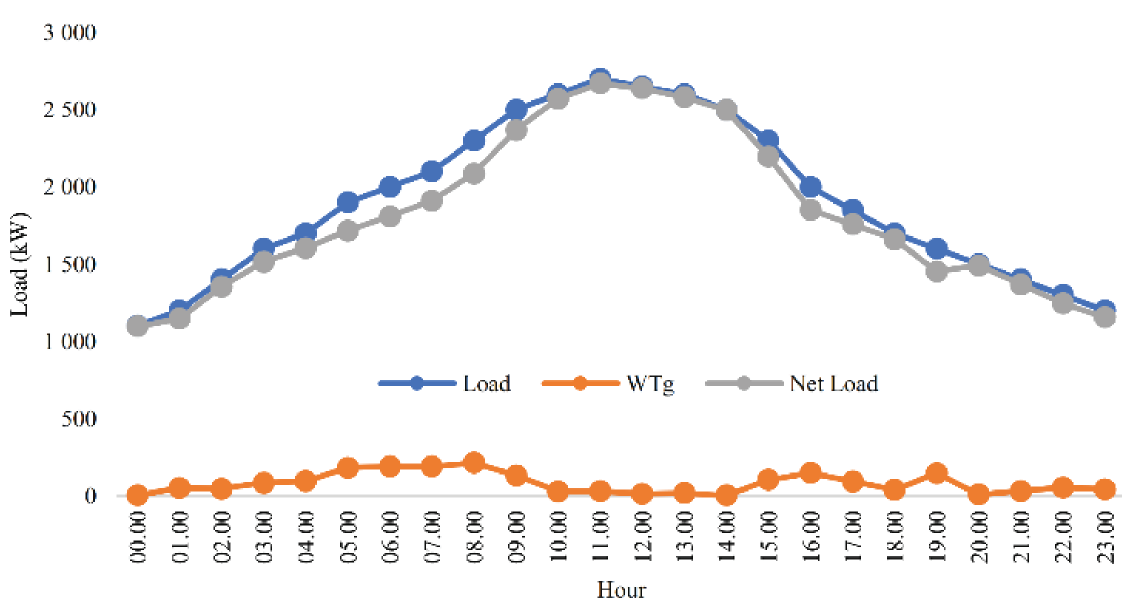

Fig. 2. Load pattern.

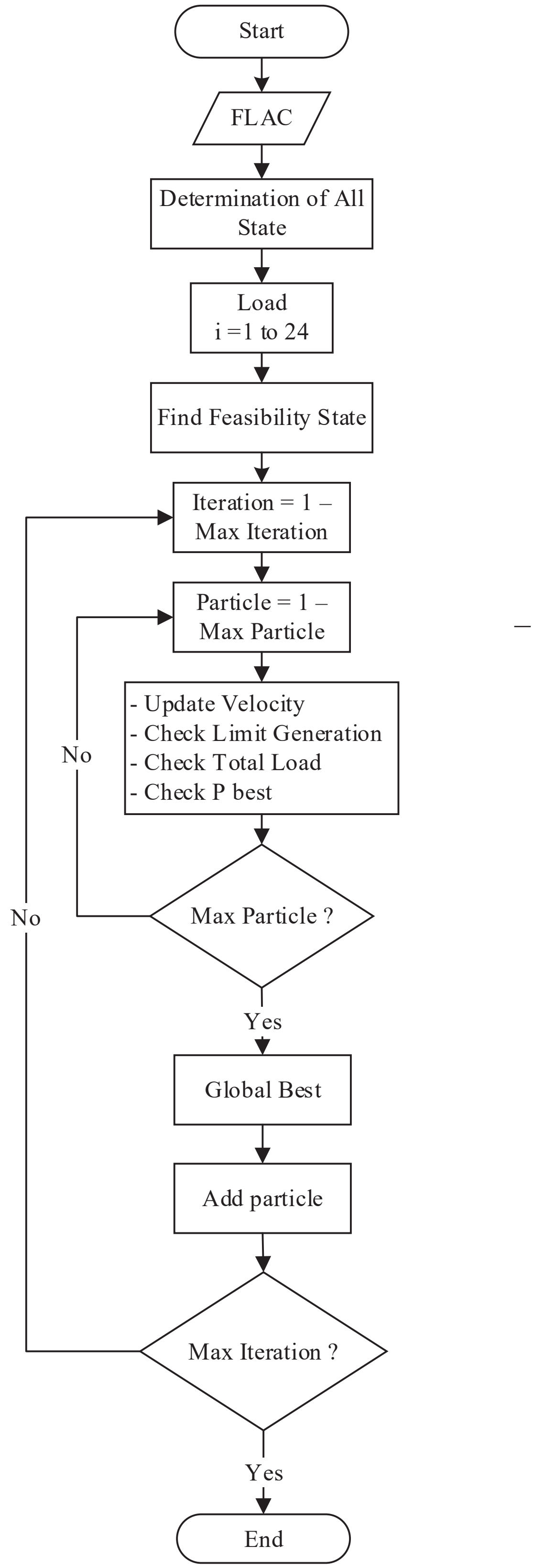

Fig. 3. IPSO flowchart.

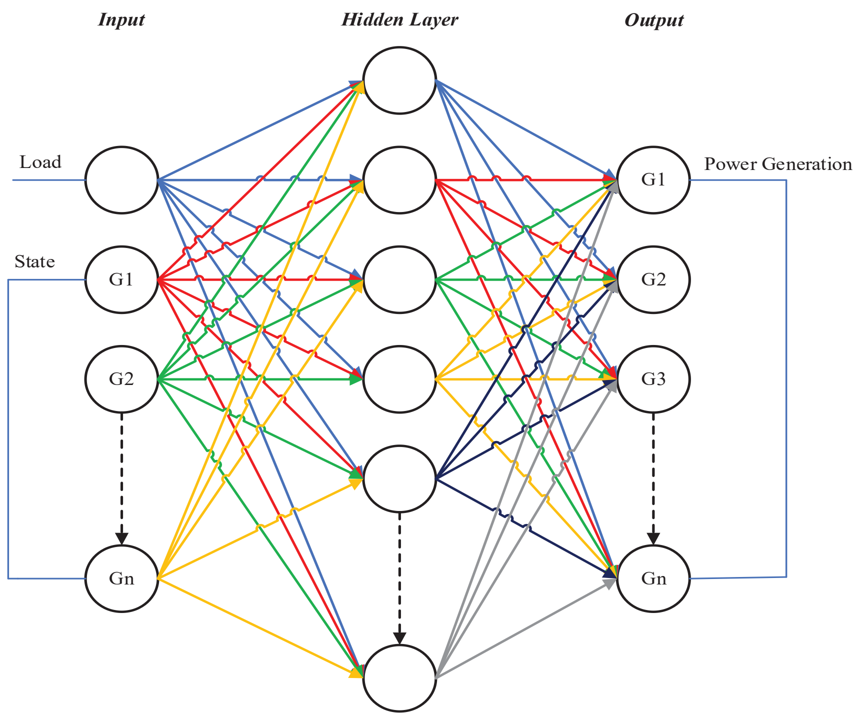

Fig. 4. DL construction.

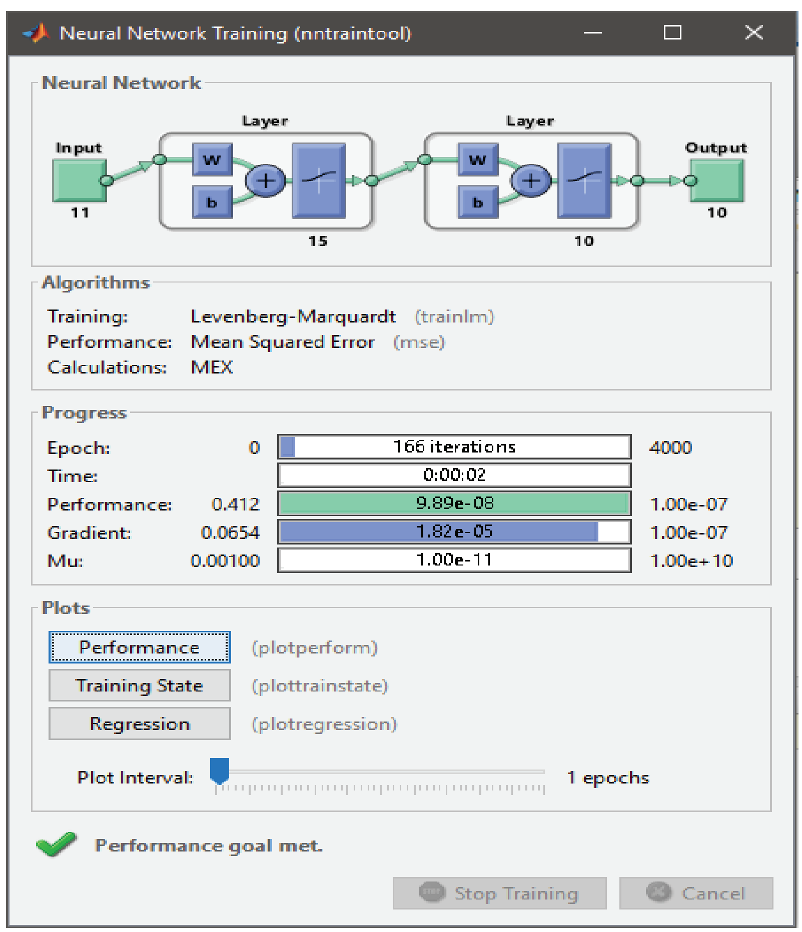

Fig. 5. DL train proses.

Table 3. Data of input train DL.

Load (kW)	1 055	1 072	1 097	1 100	>>	2 637	2 650	2 670	2 700
Unit 1	1	1	1	1		1	1	1	1
Unit 2	1	1	1	1		1	1	1	1
Unit 3	1	1	1	1		1	1	1	1
Unit 4	1	1	1	1		1	1	1	1
Unit 5	1	1	1	1	>>	1	1	1	1
Unit 6	1	1	1	1		1	1	1	1
Unit 7	1	1	1	1		1	1	1	1
Unit 8	1	1	1	1		1	1	1	1
Unit 9	1	1	1	1		1	1	1	1
Unit 10	1	1	1	1		1	1	1	1

Table 4. IPSO output both before and after WTs is affected.

Time (hours)	Before wind is affected		After wind is affected	
	Load (kW)	IPSO	Load (kW)	IPSO
1	1 100	1 100	1 097	1 097
2	1 200	1 200	1 148	1 148
3	1 400	1 400	1 355	1 355
4	1 600	1 600	1 515	1 515
5	1 700	1 700	1 604	1 604
6	1 900	1 900	1 717	1 717
7	2 000	2 000	1 809	1 809
8	2 100	2 100	1 910	1 910
9	2 300	2 300	2 086	2 086
10	2 500	2 500	2 368	2 368
11	2 600	2 600	2 572	2 572
12	2 700	2 700	2 670	2 670
13	2 650	2 650	2 637	2 637
14	2 600	2 600	2 582	2 582
15	2 500	2 500	2 498	2 498
16	2 300	2 300	2 197	2 197
17	2 000	2 000	1 852	1 852
18	1 850	1 850	1 757	1 757
19	1 700	1 700	1 661	1 661
20	1 600	1 600	1 452	1 452
21	1 500	1 500	1 491	1 491
22	1 400	1 400	1 369	1 369
23	1 300	1 300	1 246	1 246
24	1 200	1 200	1 156	1 156

Table 7. Data of output train DL.

Load (kW)	1 055	1 072	1 097	1 100	>>	2 637	2 650	2 670	2 700
Unit 1	355	372	397	400		600	600	600	600
Unit 2	100	100	100	100		600	600	600	600
Unit 3	100	100	100	100		400	400	400	400
Unit 4	100	100	100	100		387	400	400	400
Unit 5	50	50	50	50		300	300	300	300
Unit 6	100	100	100	100	>>	100	100	120	150
Unit 7	100	100	100	100		100	100	100	100
Unit 8	50	50	50	50		50	50	50	50
Unit 9	50	50	50	50		50	50	50	50
Unit 10	50	50	50	50		50	50	50	50

Table 8. DL output both before and after WTs is affected.

Time (hr)	Before wind is affected		After wind is affected	
	Load (kW)	DL	Load (kW)	DL
1	1 100	1 100	1 097	1 097
2	1 200	1 201	1 148	1 148
3	1 400	1 401	1 355	1 356
4	1 600	1 601	1 515	1 515
5	1 700	1 700	1 604	1 605
6	1 900	1 901	1 717	1 717
7	2 000	2 000	1 809	1 809
8	2 100	2 100	1 910	1 910
9	2 300	2 301	2 086	2 086
10	2 500	2 500	2 368	2 368
11	2 600	2 599	2 572	2 572
12	2 700	2 700	2 670	2 670
13	2 650	2 651	2 637	2 638
14	2 600	2 600	2 582	2 582
15	2 500	2 500	2 498	2 498
16	2 300	2 301	2 197	2 198
17	2 000	2 000	1 852	1 852
18	1 850	1 850	1 757	1 758
19	1 700	1 700	1 661	1 661
20	1 600	1 601	1 452	1 452
21	1 500	1 500	1 491	1 491
22	1 400	1 401	1 369	1 369
23	1 300	1 300	1 246	1 246
24	1 200	1 201	1 156	1 156

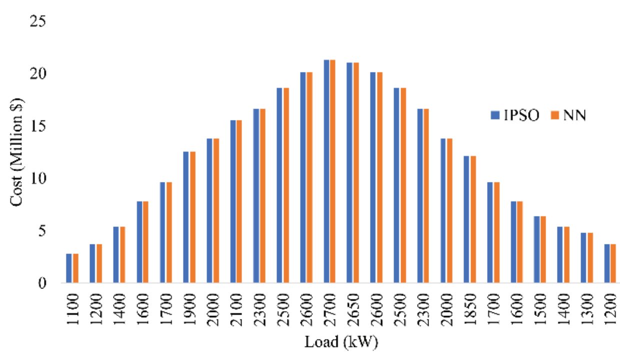

Fig. 6. Total cost before the wind is affected

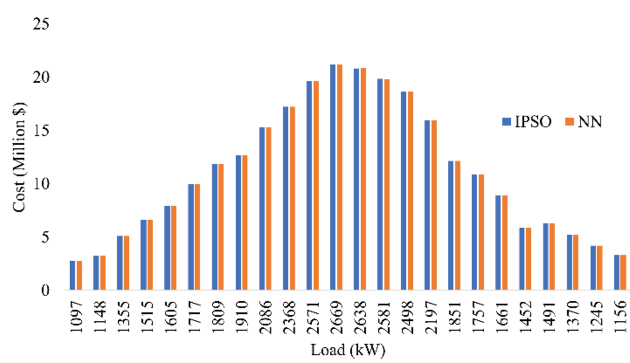

Fig. 7. Total cost after the wind is affected

structure is regulated with 15 neurons. The training process needs almost 2 h to finish. After the training process is successful, DL is tested as an economic dispatch function that replaces IPSO both before and after the WTs are affected. As shown in Table 8, all hour load both before and after WTs is affected, DL can produce a total load according to each hour of loading. DL can produce total power generation equal to or slightly higher than the load should be.

3.3 Total Cost Results

After checking the total generation process in this chapter shown the results of the total cost data as the objective function in this research from before wind is affected the system as shown in Figure 6 and after as shown in Figure 7. Because the total generation from both methods is quite the same, the total cost from both methods too in every each hour. The reduction of total cost from before wind is affected and after are USD 22.86 Million for IPSO and USD 22.89 Million for DL.

3.4 Comparison of ED IPSO and ED DL

Based on the test results of IPSO and DL is shown a good result but the execution time from these two methods are very different. IPSO produces an average execution time of more than 30 min in 10 ED tests with 24 h of loading and DL managed to speed up ED IPSO execution time to 3.5 s on average in 10 tests. The effect of WTs has an impact on the total load that must be generated by the thermal generator and the total cost generated by the thermal generator.

3.5 Future research

The wind turbine (WTs) in this study is one of the RE. In future research, the application of a microgrid with several other REs will be studied, including solar panels, biogas, and others [33–41].

5. CONCLUSION

AIPSO shows good results in the ED process, being able to generate according to the feasibility state with total generation according to the total targeted load, but IPSO produces a long enough execution time of 30 min on average in 10 tests. DL structure in this research successfully replaces the ED function in the IPSO method, by producing the same output with load or slightly higher than the load should be and being able to accelerate execution time to 3.5 s on average in 10 tests. From the total cost side, wind energy is affecting the reduction cost for USD 22.86 Million as the result of IPSO and USD 22.89 Million as the result from DL.

6. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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