A New Optimal Operation Structure For Renewable- Based Microgrid Operation based On Teaching Learning Based Optimization Algorithm

Tavakoli, Amir and Mirzaei, Farzad and Tashakori, Sajad

Azad University of Shiraz

26 September 2018

A New Optimal Operation Structure For Renewable- Based Microgrid Operation based On Teaching Learning Based Optimization Algorithm

Amir Tavakoli, Farzad Mirzaei, Sajad Tashakori

Azad University of Shiraz, Shiraz, Iran

Abstract: This paper proposes a new optimization framework for the optimal power dispatch in both grid-connected and islanded microgrid modes. Solving the microgrid operation by the evolutionary algorithms can be faster than analytical models due to the complexity of the problem. To demonstrate the efficiency and high performance of the proposed technique, it is applied on the IEEE 33 bus test network. Also, the proposed technique is compared with the analytical model, and also well-known heuristic methods such as particle swarm optimization (PSO), genetic algorithm (GA).

I. Introduction

In the recent years, renewable energies are emerged varies research science due to some significant advantages such as security, sustainability, and environment-friendly [1], [2]. Along with many advantages, there exist some significant challenging associated with the renewable energies such as unpredictability, and their dependency on the weather conditions.

By emerging the renewable energies into the power system, the microgrids has been attracted a lot of attention due to their high potential in using the renewable energies. In the power system operation, the microgrid can be defined as the summation of the loads and distributed energy resources that can operate in both connected and islanded modes [3]- [6]. Microgrid has many advantages such as closeness to the consumers, lower operation cost, higher reliability, higher resiliency, and lower transmission cost due to less transmission line. However, the stable operation and malfunction are the most challenging issues in the microgrid.

Up to now, many types of research have been done for the optimal operation of the microgrid. For instance, the market-based microgrid is investigated in [7] where the authors used the mathematical modeling known as the mixed integer linear programming [8] to simplify and address the problem. A novel energy harvesting techniques based on the [9], [10] are studied in [11] the optimal energy scheduling of microgrid. It is worth noting that in the microgrid operation the time decision to islanding the network and also optimal dispatch is very important. Hence, in the microgrid operation, heuristics methods are more efficient than other techniques due to their higher speed in decision making. For instance, in [25] the optimal operation of a microgrid is obtained by genetic algorithm (GA). In [13] the particle swarm optimization (PSO) is utilized for the optimal operation of the microgrid. This paper proposes a new evolutionary algorithm for the microgrid operation based on the teaching learning-based optimization (TLBO) [14-16]. Although many evolutionary algorithms exist [17-25], but TLBO is selected due to two phases of research in the algorithm as explained in section III [26-28].

II. Problem Formulation

The proposed optimization problem is associated with an objective function and constraints as follows:

A. Objective function

The main objective is to minimize the total operation cost as,

$$Min \sum_{t} \sum_{i} (F_i(P_{it}) I_{it} + SU_{it} + SD_{it}) + \sum_{t} \rho_t P_{M,t} \tag{1}$$

where *t* is the time *F* is the cost coefficient, *P* is the power, *i* is the number of generators, *SU* and *SD* are the startup and shutdown costs respectively, ρ is the cost of power purchased from the main grid and *M* denotes the main grid.

B. Constraints

The proposed optimization problem is associated with some significant constraints as (2)- (8). Equation (2) presents the power balance constraint. Indeed, this constraint claims that the total generation and purchasing power should be equal to demand at any time interval (*D* denotes as the total load at hour *t*). Constraint (3) assure that the purchasing power from the main grid should be within a limit. Constraint (4) guarantees that the output power of each generation units should be within a limit. Also, integer variable *I* is defined to determine the status of generation units in any time, and it is zero when a unit is off, and it is one when a unit is on. Also, the ramp up/down (*UR/DR*) limitations are defined in (5) and (6) respectively. Equations (7) and (8) declare the Minimum up/downtime constraint where T^{on} and T^{off} are numbers of successive on and off hours respectively.

$$\sum_{i} P_{it} + P_{Mt} = \sum_{d} D_{dt} \qquad \forall t \tag{2}$$

$$-P_M^{max} \leq P_{M,t} \leq P_M^{max} \qquad \forall t \tag{3}$$

$$P_i^{min} I_{it} \leq P_{it} \leq P_i^{max} I_{it} \qquad \forall i \in G, \forall t \tag{4}$$

$$P_{it} - P_{i(t-1)} \leq UR_i \qquad \forall i \in G, \forall t \tag{5}$$

$$P_{i(t-1)} - P_{it} \leq DR_i \qquad \forall i \in G, \forall t \tag{6}$$

$$UT_i(I_{it} - I_{i(t-1)}) \leq T_{it}^{on} \qquad \forall i \in G, \forall t \tag{7}$$

$$DT_i(I_{i(t-1)} - I_{it}) \leq T_{it}^{off} \qquad \forall i \in G, \forall t \tag{8}$$

III. Teaching Learning Based Optimization

Teaching Learning Based Optimization has been explained in the year 2011 which is an evolutionary algorithm [16]. This approach is applied in different optimization problems like mechanical system problems optimization [16] and continues nonlinear large-scale problems optimization [17].

This approach which is similar to the other evolutionary approaches is based on population. The population in this approach is completely related to the class population. First, two phases need to be defined.

1) Teaching Phase

2) Learner Phase

Certainly, each student in the class can develop his knowledge based on the mentioned steps: Initially, learning from the teacher of the class and enhancing his knowledge. Then, interaction with other students in the class to improve the knowledge. The first part of this method can be defined as the teacher phase and the second part of this method can be defined as the learner phase.

In this paper, TLBO is applied for unit commitment issue. Actually, the mean value of the first optimization results is considered as a teacher of a class. Next, in the second iteration, the determined result is compared with the other results. If the newly determined result is better than the previous one, it should be exchanged otherwise it is going to be rejected. The difference between knowledge of and their teacher is expressed in equation (9):

$$d\mu^k = T^k - TF^k \mu^k \tag{9}$$

where μ^k denotes the mean value for the class and parameter TF^k denotes the teaching factor which can be considered as a random variable of 1 or 2. Thus we have:

$$X_{n,j}^k = X_{p,j}^k + rand(d\mu^k) \tag{10}$$

The combinations of units need to be analyzed in the next phase. Hence, the cost of all the possible units' combination needs to be computed to find the optimal outcome. Therefore, the following expression can be expressed as follows:

$$X_n = \begin{Bmatrix} X_j + rand(\Delta X_{i-j}) & f(X_j) < f(X_i) \\ X_j + rand(\Delta X_{i-j}) & else \end{Bmatrix} \tag{11}$$

If the newly determined result is better than the previous one, it needs to be replaced else it needs to be rejected. The algorithm of TLBO is illustrated in figure 1.

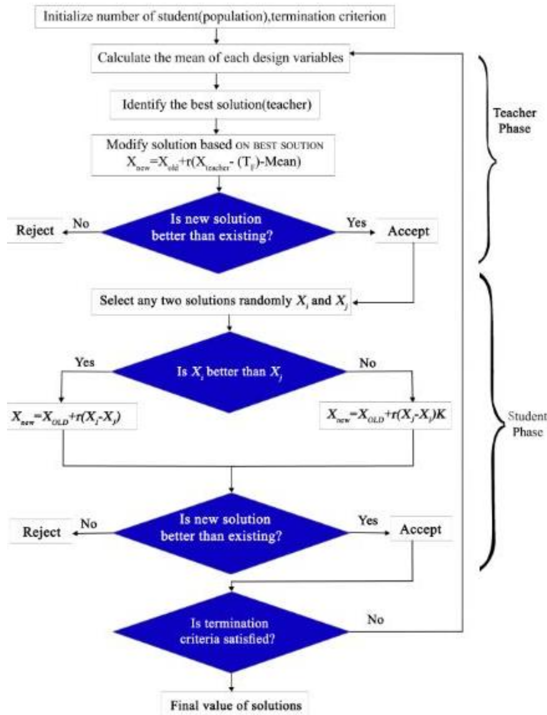

Fig. 1. TLBO flowchart

IV. Simulation Results

The proposed optimization problem is tested on a modified IEEE 32 bus test network contains two wind turbines (WT), and four distributed generators (DGs) as Fig. 2. The proposed technique is applied to the islanded mode where the main breaker is open.

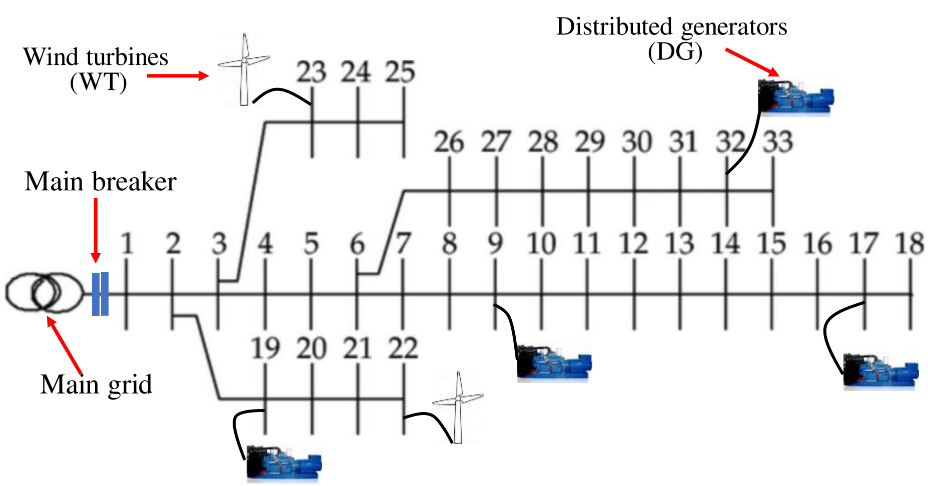

Fig. 2. Single line diagram of the modified IEEE 33 bus test network

Table I represents the WTs output power for the entire horizon which is 24 hours (day-ahead).

Table I. WTs output power

Hour	1	2	3	4	5	6	7	8	9	10	11	12
WT#1 (KW)	220	220	220	220	220	170	220	190	300	400	620	760
WT#2 (KW)	180	180	180	180	180	140	180	170	250	300	590	595
Hour	13	14	15	16	17	18	19	20	21	22	23	24
WT#1 (KW)	790	600	240	225	170	220	200	220	180	180	160	120
WT#2 (KW)	540	480	180	165	190	160	165	180	150	150	140	100

Also, the distributed generation information is provided in Table II.

Table II. Distributed generation

DG Number	Capacity (MW)	Cost ($/kWh)
DG1	20000-45000	0.17
DG2	21000-33000	0.21
DG3	10000-21000	0.32
DG4	7000-40000	0.43

The load for the entire horizon is represented in Fig. 3.

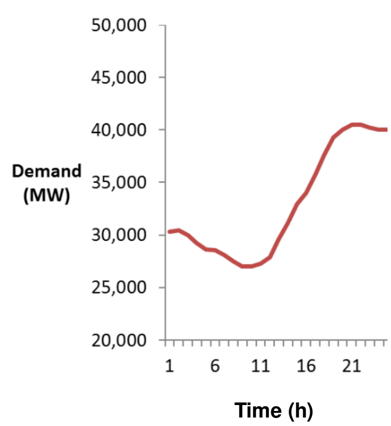

Fig. 3. Load demand for 24 hours.

By applying the TLBO, the status of the DG can be obtained as Table III. Based on this table, the cheapest units (DG1 and 2) are committed more than others. Also, the most expensive unit (DG4) is off in the entire horizon. However, this DG is considered for the rainy days.

Table III. Status of DG for 24 hours

Hour	1	2	3	4	5	6	7	8	9	10	11	12
DG1	1	1	1	1	1	1	1	1	1	1	1	1
DG2	1	1	1	1	1	1	1	1	1	1	1	1
DG3	0	0	0	0	0	0	0	0	0	0	0	1
DG4	0	0	0	0	0	0	0	0	0	0	0	0
Hour	13	14	15	16	17	18	19	20	21	22	23	24
DG1	1	1	1	1	1	1	1	1	1	1	1	1
DG2	1	1	1	1	1	1	1	1	1	1	1	1
DG3	1	1	1	1	1	1	1	1	0	0	0	0
DG4	0	0	0	0	0	0	0	0	0	0	0	0

Table IV compared the total operational cost of the proposed method with MILP, GA, and PSO algorithms. Although the operational cost of the MILP is lower, the time solution of the proposed method is faster than others, and the difference cost is not significant.

Method	Cost (M$)	Time to solve (s)
TLBO	24,283	11.1
PSO	27,342	32.2
GA	25,457	27.4
MILP	23,936	15.3

Conclusion

This paper proposed a new approach for optimal operation of a microgrid in the islanded mode based on the new heuristic technique which is known as the teaching learning-based optimization. The proposed method is compared with both analytical and well-known heuristic methods such as PSO and GA. Based on the results, compared to the evolutionary algorithms, the proposed technique is faster with the less operational cost. However, compared to the MILP as a mathematical model, the price of the method is higher. This price would be not considered due to its faster solution time which plays a very significant role in the islanded microgrid.

References

[1] Jahangiri, Vahid, and Mir Mohammad Ettefagh. "Multibody Dynamics of a Floating Wind Turbine Considering the Flexibility Between Nacelle and Tower." International Journal of Structural Stability and Dynamics 18, no. 06 (2018): 1850085.

[2] Ashkaboosi, Maryam, Seyed Mehdi Nourani, Peyman Khazaei, Morteza Dabbaghjamanesh, and Amirhossein Moeini. "An optimization technique based on profit of investment and market clearing in wind power systems." American Journal of Electrical and Electronic Engineering 4, no. 3 (2016): 85-91.

[3] Dabbaghjamanesh, Morteza, Shahab Mehraeen, Abdollah Kavousi Fard, and Farzad Ferdowsi. "A New Efficient Stochastic Energy Management Technique for Interconnected AC Microgrids." arXiv preprint arXiv:1803.03320 (2018).

[4] Parhizi, Sina, Hossein Lotfi, Amin Khodaei, and Shay Bahramirad. "State of the Art in Research on Microgrids: A Review." Ieee Access 3, no. 1 (2015): 890-925.

[5] Khodaei, Amin, and Mohammad Shahidehpour. "Microgrid-based co-optimization of generation and transmission planning in power systems." IEEE transactions on power systems 28, no. 2 (2013): 1582-1590.

[6] Dabbaghjamanesh, Morteza, Abdollah Kavousi-Fard, and Shahab Mehraeen. "Effective Scheduling of Reconfigurable Microgrids with Dynamic Thermal Line Rating." IEEE Transactions on Industrial Electronics (2018).

[7] Liu, Guodong, Yan Xu, and Kevin Tomsovic. "Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization." IEEE Transactions on Smart Grid 7, no. 1 (2016): 227-237.

[8] Ghaffari, Saeed, and Maryam Ashkaboosi. "Applying Hidden Markov Model Baby Cry Signal Recognition Based on Cybernetic Theory." IJEIR 5, no. 3 (2016): 243-247.

[9] Mirab, Hadi, Reza Fathi, Vahid Jahangiri, Mir Mohammad Ettefagh, and Reza Hassannejad. "Energy harvesting from sea waves with consideration of airy and JONSWAP theory and optimization of energy harvester parameters." Journal of Marine Science and Application 14, no. 4 (2015): 440-449.

[10] Jahangiri, Vahid, Hadi Mirab, Reza Fathi, and Mir Mohammad Ettefagh. "TLP structural health monitoring based on vibration signal of energy harvesting system." Latin American Journal of Solids and Structures 13, no. 5 (2016): 897-915.

[11] Zhang, Yu, Nikolaos Gatsis, and Georgios B. Giannakis. "Robust energy management for microgrids with high-penetration renewables." IEEE Transactions on Sustainable Energy 4, no. 4 (2013): 944-953.

[12] Liao, Gwo-Ching. "Solve environmental economic dispatch of Smart MicroGrid containing distributed generation system–Using chaotic quantum genetic algorithm." International Journal of Electrical Power & Energy Systems 43, no. 1 (2012): 779-787.

[13] Bevrani, Hassan, F. Habibi, P. Babahajyani, Masayuki Watanabe, and Yasunori Mitani. "Intelligent frequency control in an AC microgrid: Online PSO-based fuzzy tuning approach." IEEE transactions on smart grid 3, no. 4 (2012): 1935-1944.

[14] Dabbaghjamanesh, M., A. Moeini, M. Ashkaboosi, P. Khazaei, and K. Mirzapalangi. "High performance control of grid connected cascaded H-Bridge active rectifier based on type II-fuzzy logic controller with low frequency modulation technique." International Journal of Electrical and Computer Engineering (IJECE) 6, no. 2 (2016): 484-494.

[15] Khazaei, Peyman, Morteza Dabbaghjamanesh, Ali Kalantarzadeh, and Hasan Mousavi. "Applying the modified TLBO algorithm to solve the unit commitment problem." In World Automation Congress (WAC), 2016, pp. 1-6. IEEE, 2016.

[16] Rao, Ravipudi V., Vimal J. Savsani, and D. P. Vakharia. "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems." Computer-Aided Design 43, no. 3 (2011): 303-315.

[17] Zitzler, Eckart, Marco Laumanns, and Lothar Thiele. "SPEA2: Improving the strength Pareto evolutionary algorithm." TIK-report 103 (2001).

[18] Angeline, Peter J., Gregory M. Saunders, and Jordan B. Pollack. "An evolutionary algorithm that constructs recurrent neural networks." IEEE transactions on Neural Networks 5, no. 1 (1994): 54-65.

[19] Khazaei, P., S. M. Modares, M. Dabbaghjamanesh, M. Almousa, and A. Moeini. "A high efficiency DC/DC boost converter for photovoltaic applications." International Journal of Soft Computing and Engineering (IJSCE) 6, no. 2 (2016): 2231-2307.

[20] Rakhshan, Mohsen, Navid Vafamand, Mokhtar Shasadeghi, Morteza Dabbaghjamanesh, and Amirhossein Moeini. "Design of networked polynomial control systems with random delays: sum of squares approach." International Journal of Automation and Control 10, no. 1 (2016): 73-86.

[21] Prins, Christian. "A simple and effective evolutionary algorithm for the vehicle routing problem." Computers & Operations Research 31, no. 12 (2004): 1985-2002.

[22] Droste, Stefan, Thomas Jansen, and Ingo Wegener. "On the analysis of the (1+ 1) evolutionary algorithm." Theoretical Computer Science 276, no. 1-2 (2002): 51-81.

[23] Dabbaghjamanesh, Morteza, Shahab Mehraeen, Abdollah Kavousifard, and Mosayeb Afshari Igder. "Effective scheduling operation of coordinated and uncoordinated wind-hydro and pumped-storage in generation units with modified JAYA algorithm." In Industry Applications Society Annual Meeting, 2017 IEEE, pp. 1-8. IEEE, 2017.

[24] Van Veldhuizen, David A., and Gary B. Lamont. "On measuring multiobjective evolutionary algorithm performance." In Evolutionary Computation, 2000. Proceedings of the 2000 Congress on, vol. 1, pp. 204-211. IEEE, 2000.

[25] Yen, Gary G., and Haiming Lu. "Dynamic multiobjective evolutionary algorithm: adaptive cell-based rank and density estimation." IEEE Transactions on Evolutionary Computation7, no. 3 (2003): 253-274.

[26] Taherzadeh, Erfan, Morteza Dabbaghjamanesh, Mohsen Gitizadeh, and Akbar Rahideh. "A New Efficient Fuel Optimization in Blended Charge Depletion/Charge Sustenance Control Strategy for Plug-in Hybrid Electric Vehicles." IEEE Transactions on Intelligent Vehicles (2018).

[27] Ashkaboosi, Maryam, Farnoosh Ashkaboosi, and Seyed Mehdi Nourani. "The Interaction of Cybernetics and Contemporary Economic Graphic Art as" Interactive Graphics"." (2016).

[28] Ghaffari, Saeed, and M. Ashkaboosi. "Applying Hidden Markov M Recognition Based on C." (2016).