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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.

$$\sum_i P_{it} + P_{Mt} = \sum_d D_{dt} \qquad \forall t \tag{2}$$

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

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

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

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

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

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

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:

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

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.
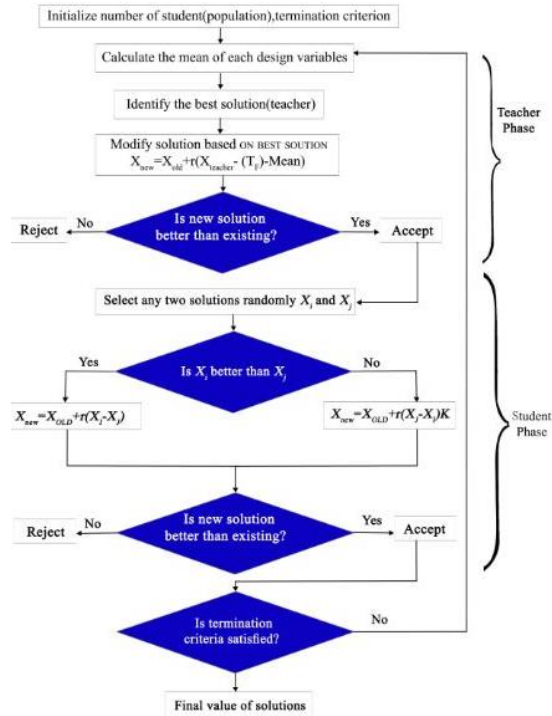
Fig. 1. TLBO flowchart

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.
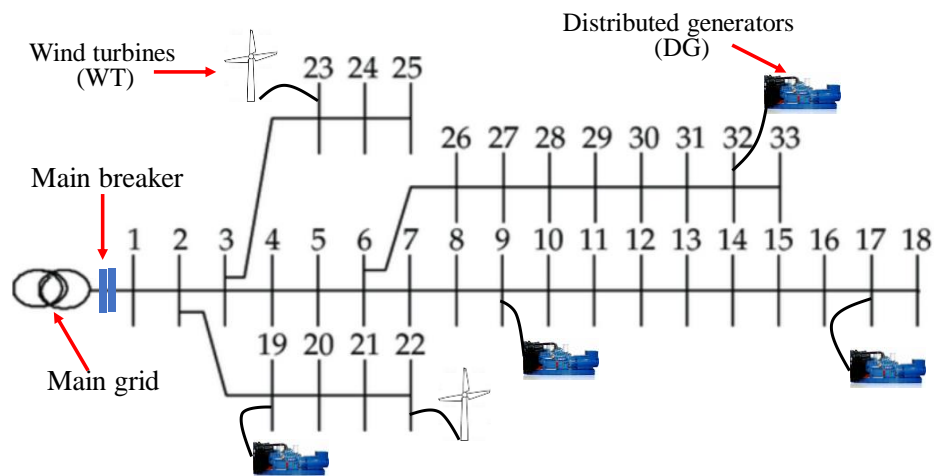

Fig. 2. Single line diagram of the modified IEEE 33 bus test network

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

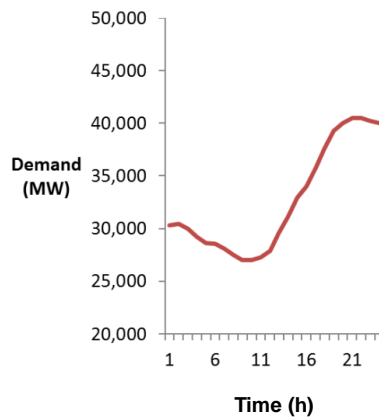The load for the entire horizon is represented in Fig. 3.

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.

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