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Optimal Energy Management of Microgrids using Quantum Teaching Learning Based Algorithm

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ABSTRACT: The most important challenge in microgrids is the coordination of distributed energy resources (DERs), due to the existence of several DERs with fugacious characteristics. In this paper, a robust frame associated with a quantum version of the Teaching-Learning-Based Optimization (quantum TLBO) algorithm is proposed for the first time for the microgrid optimal energy management problem. Uncertainties in the load and the output power of renewable energy sources are modeled using robust optimization (RO). The operation cost of the microgrid is considered as an objective function. The problem is formulated as a bi-level minimum-maximum optimization problem and is solved in two levels iteratively. First, by maximizing the operation cost of the microgrid, the worst case for the uncertain parameters is determined using Particle Swarm Optimization (PSO). Then, according to the results obtained in the first level, by minimizing the operation cost of the microgrid, the final optimal solution is obtained using the Quantum TLBO (QTLBO). This approach is applied to a grid-connected microgrid consisting of renewable energy sources, microturbines, fuel cells, and battery systems. The obtained simulation results demonstrate that the QTLBO is significantly superior to the TLBO, Differential Evolution, and Real-Coded Genetic Algorithm in terms of both achieving the final optimal solution and convergence speed.

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1- Introduction

The expansion of global deployment of distributed energy resources (DERs) has led to the development and increase of smart microgrids, energy hubs, etc. [1]. The use of microgrids reduces losses due to the transmission and distribution of electrical energy and provides cheaper electrical energy. Since the microgrid can be disconnected from the main grid and operated as an island, it can prevent global blackouts in emergencies. Therefore, making the power supply more reliable [2].

With the transformation of traditional passive distribution networks into active distribution networks, microgrid energy management has become an important and popular research area [1]. Researchers have studied energy management systems (EMSs) in a variety of studies to minimize production costs, minimize transmission or distribution losses, reduce pollution, and optimize operating and maintenance costs [1, 3].

The optimization of microgrid operation costs is the main requisite of microgrid EMS. Various optimization methods are proposed to solve this problem, which can be divided into two categories: 1) mathematical optimization; 2) heuristic and meta-heuristic optimization [1].

In [4-11], mixed integer linear programming (MILP) is used to optimize output power to minimize operation costs in a microgrid. Also, the mixed integer nonlinear programming (MINLP) model [12-14] and the dynamic programming method [15] are used to ensure that the operation costs in the energy management problem are minimal. In [16-19], the Robust Optimization (RO) approach is utilized to manage microgrid energy under uncertainties in consumption, production, and power price. Studies on the use of predictive control methods for microgrid operation optimization are presented in [20-23].

So far, various meta-heuristic methods have been used to solve the problem of optimizing energy management in microgrids. These methods include: Particle Swarm Optimization (PSO) [24-26], Modified Particle Swarm Optimization (MPSO) [27], Regrouping Particle Swarm Optimization (RegPSO) [28], Multi-Objective Particle Swarm Optimization (MOPSO) [25], Self-adaptive modification technique based on θ-Particle Swarm Optimization (θ-PSO) algorithm [29], Modified Bat Algorithm (MBA) [30], Ant Colony Optimization (ACO) [31], Artificial Bee Colony (ABC) [3], Group Search Optimization (GSO) [32], Crow Search Algorithm (CSA) [33], Efficient Salp Swarm

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Algorithm (ESSA) [34], a new version of Krill Herd (KH) called θ-Modified Krill Herd (θ-MKH) [35], Water Cycle Algorithm (WCA) [36], Gravitational Search Algorithm (GSA) [36], Grey Wolf Optimizer (GWO) and Taguchi [14], Genetic Algorithm-Simulated Annealing (GA-SA) hybrid method [37], Firefly Algorithm (FA) [38], Differential Evolution (DE) algorithm [39, 40], Chaos enhanced differential evolution algorithm [41], Teaching-Learning Based Optimization (TLBO) [38], and Modified Teaching–Learning Based Optimization (MTLBO) [42, 43].

Unlike mathematical programming methods, classical meta-heuristic algorithms can solve indistinguishable and multi-dimensional problems. However, there is no guarantee that classical meta-heuristic algorithms will achieve the optimal global solution [1]. Integrating population-based evolutionary computing with quantum computing leads to the increased performance of traditional meta-heuristic algorithms [1]. Recently, in [1], for the first time, a quantum version of the TLBO (quantum TLBO) is proposed to solve the problem of microgrid optimal energy management.

Uncertainties have adverse effects on optimization issues. Hence, modeling the uncertainty in input parameters in optimization problems is an important issue [44]. Various methods are suggested in different research to consider the uncertainties due to the random behavior of renewable energy sources, or the uncertainties in the parameters that are unclear. For example, the methods that are suggested to model the uncertainties of the power of renewable distribution generations, price of electricity, and loads include probabilistic programming based on Monte Carlo [38], RO [16, 17], stochastic optimization [1, 25, 30, 32], and different point estimate methods [26, 29, 34, 35, 38, 45, 46]. The point estimation techniques are approximate methods that are not accurate enough to predict errors; because they are dependent on sampling data derived from distinct scenarios [1].

Defining suitable probabilistic models for stochastic parameters is challenging [47]. In stochastic optimization, the obtained solutions are probabilistic and may not occur [44]. The obtained solution via the stochastic optimization will be optimal only for the introduced scenarios. However, the obtained solution through the RO will be optimal in all possible realizations for uncertain parameters [48]. Stochastic optimization requires a large number of scenarios to ensure the quality of the scheduling solution. Therefore, in addition to increasing the size of the problem, the amount of computation increases. While RO considers only the worst-case scenario and stays computable for all cases [48]. Scenario generation technique in stochastic optimization affects the accuracy of the solution; while RO just requires data about the lower bound and upper bound [48]. Hence, RO has become particularly popular because it does not require a lot of assumptions about probability. The RO method obtains an optimal solution that protects the system against any result in a given set of uncertainties [47]. In other words, it is sufficient to know the bounds of the uncertain parameters. Therefore, uncertainty modeling using the RO technique is more accessible than stochastic optimization [44]. In [45], load demand uncertainties are modeled using the RO method. Extensive analysis of microgrid energy management is performed under two frameworks of RO based on prediction intervals and optimization based on predicted values [49].

A review of the above literature indicates that so far only one paper has used a quantum algorithm to solve the problem of microgrid optimal energy management. That paper has used stochastic optimization to consider the uncertainty in the output of PV and WT. In this work, a robust framework shared with the quantum TLBO (QTLBO) algorithm is proposed for the first time to solve the problem of microgrid optimal energy management. Uncertainty in the load and uncertainties in the PV and WT output powers are modeled using RO. The objective function that is minimized in this work is the operation cost of the microgrid. To achieve a solution close to the global optimal solution, the problem is formulated as a bi-level problem. In the first level, the objective function is maximized to determine the worst case for the uncertainty parameters. At the next level, the cost function is minimized to find the optimal solution. The PSO algorithm is used to maximize the objective function and the QTLBO algorithm is used to minimize the objective function. Also, besides the QTLBO algorithm, the TLBO, Real-Coded Genetic Algorithm (RCGA), and DE algorithms are used to probe the effectiveness of the QTLBO algorithm.

The main contributions of this paper are:

The RO method is combined with the QTLBO algorithm to solve the microgrid optimal energy management problem for the first time. Thus, the RO method is applied to model uncertainties in renewable energy sources and load. Then, the QTLBO algorithm is applied to solve the energy management problem.

The graph of the QTLBO algorithm results based on the number of runs is produced which demonstrates the effectiveness of the QTLBO algorithm.

The results of the QTLBO algorithm, TLBO algorithm, DE algorithm, and RCGA are compared together to show the effectiveness of the QTLBO algorithm.

The structure of the paper is as follows in Section 2, the microgrid modeling is given. The Robust Optimization for Uncertainty Modelling is presented in Section 3. Section 4 describes the TLBO and QTLBO algorithms. Section 5 is devoted to the simulation results and discussion. Finally, Section 6 deals with the conclusion.

2- Microgrid modeling

The microgrid considered in this paper is a grid-connected microgrid consisting of wind turbine (WT), photovoltaic (PV), fuel cell (FC), microturbine (MT), and battery energy storage system (BESS). It is shown in Fig. 1. The microgrid central controller (MGCC) is responsible for controlling the energy exchange between the microgrid and the main grid [1].

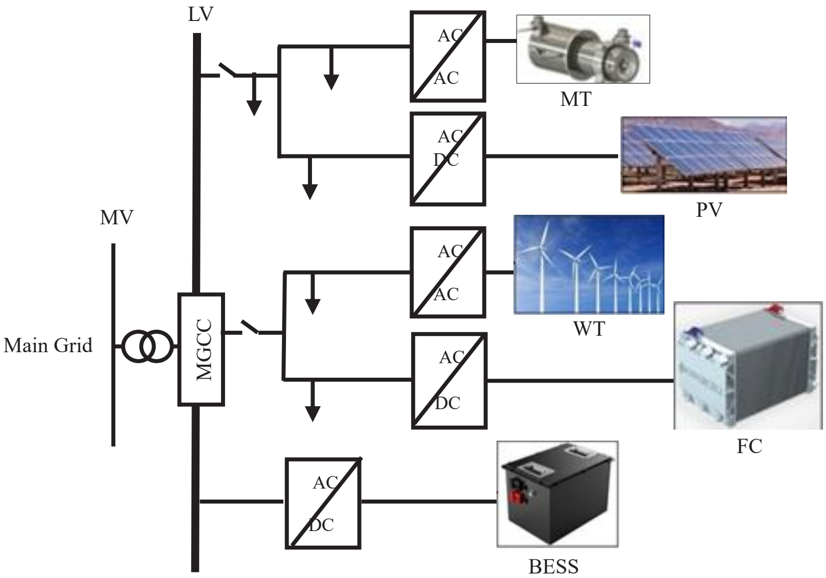


Fig. 1. A typical microgrid

2- 1- Problem formulation

2- 1- 1- Objective function

In the present paper, the energy produced by renewable sources and the energy stored by battery are optimized by microgrid energy management problems to ensure that operating costs are minimal. Thus, the aim is to minimize the objective function defined in the optimization problem (1). Problem decision variables are designated by X where X={ $P_{DG_i}^t$, $P_{BESS_j}^t$, p_{grid}^t , u_i^t , v_j^t }.

$$Min\, f(X) = \sum_{t=1}^{T} Operation\, \text{Cos}\, t^t = \sum_{t=1}^{T} OC^t$$

$$= \sum_{t=1}^{T} \left\{ \sum_{i=1}^{NG} \left[u_i^t P_{DG_i}^t B_{DG_i}^t + S_{DG_i} \left| u_i^t - u_i^{t-1} \right| \right] + \right. \tag{1}$$

$$\sum_{j=1}^{NS} \left[v_j^t P_{BESS_j}^t B_{BESS_j}^t + S_{BESS_j} \left| v_j^t - v_j^{t-1} \right| \right] + p_{gri}^t$$

where, t illustrates time in hours, and T is 24. u_i^t and v_j^t indicates the on or off states of the i^{th} distributed generation (DG) unit and the j^{th} battery storage at time t, respectively. $B_{DG_i}^t$ and $B_{BESS_j}^t$ show the bid prices of the i^{th} DG unit and the j^{th} BESS unit at time t, for output power $P_{DG_i}^t$ and $P_{BESS_j}^t$, respectively. S_{DG_i} and S_{BESS_j} represent the costs of turning on or off the DG units and the BESS unit, respectively. B_{grid}^t displays the market price of the main grid for power P_{grid}^t at time t.

2- 1- 2- Constraints

- Power balance constraints

The generation and demand balance constraints between the microgrid power generation sources and loads are shown in Eq. (2).

$$\sum_{i=1}^{NG} P_{DG_i}^t + \sum_{j=1}^{NS} P_{BESS_j}^t + P_{grid}^t = \sum_{l=1}^{ND} P_{load_l}^t \tag{2}$$

- Limits of minimum and maximum output power

The minimum and maximum output power limits of DG units, battery storage, and main grid are given in Eq. (3).

$$\begin{cases} P_{DG_i,\min}^t \le P_{DG_i}^t \le P_{DG_i,\max}^t \\ P_{BESS_j,\min}^t \le P_{BESS_j}^t \le P_{BESS_j,\max}^t \\ P_{grid,\min}^t \le P_{grid}^t \le P_{grid,\max}^t \end{cases} \tag{3}$$

- Ramping limitation of micro-turbine

The ramping limit of the micro-turbine is in accordance with Eq. (4).

$$-DR_{MT} \le P_{MT}^t - P_{MT}^{t-1} \le UR_{MT} \tag{4}$$

where, DR_{MT} and UR_{MT} are the minimum and maximum ramp rates of the micro-turbine. P_{MT}^t and P_{MT}^{t-1} indicate the output powers of the micro-turbine at times t and t-1, respectively.

- Constraint of the main grid output power

According to Eq. (5), the output power of the main grid cannot exceed its minimum and maximum values. According to Eq. (6), a quadratic expression is added to the objective function to ensure that this constraint is satisfied and that impossible solutions are avoided [1].

$$P_{grid,l}^{t}=\begin{cases}P_{grid,\max}^{t} & \text{if } P_{grid}^{t}\succ P_{grid,\max}^{t}\\ P_{grid,\min}^{t} & \text{if } P_{grid}^{t}\prec P_{grid,\min}^{t}\\ P_{grid}^{t} & \text{if } P_{grid,\min}^{t}\le P_{grid}^{t}\le P_{grid,\max}^{t}\end{cases} \tag{5}$$

$$f(X)=\sum_{t=1}^{T}OC^{t}+\lambda_{pen}\left(P_{grid}^{t}-P_{grid,l}^{t}\right)^{2} \tag{6}$$

where, λ_{pen} is the penalty factor.

2- 2- Modeling of DGs and BESS

2- 2- 1- PV modeling

Power is generated by sunlight on the solar panel. As seen in Eq. (7), the power generated by PV depends on various parameters including panel area, absorption capacity, solar radiation intensity, and cell temperature [57].

$$P_{PV}(t)=\frac{G_s(t)}{1000}\times P_{rated}\times\eta_{PV}\times\left(1-\beta_T\left(T_{cell}-T_{C.STC}\right)\right) \tag{7}$$

where $G_s(t)$ (W/m^2) is a symbol to represent the radiant power perpendicular to the PV array surface. P_{rated} represents the panel nominal power in standard test conditions (STC). η_{PV} is in % and represents the power reduction factor of PV panels. β_T shows the PV temperature coefficient. $T_{C.STC}$ is the temperature of the cell under STC. T_{cell} is the temperature of the cell in operating conditions which can be calculated according to Eq. (8) [57].

$$T_{cell}=T_{amb}+\frac{G_s(t)}{800}\left(T_N-20\right) \tag{8}$$

where, T_{amb} is the temperature of ambient and T_N is the normal operation cell temperature.

2- 2- 2- WT modeling

According to the wind speed and the conversion of speed to power, the output power of the wind turbine is obtained in the form of Eq. (9) [57].

$$P_{WT}=\begin{cases}0 & \text{if } v_{WT}\prec v_{WT,cut-in} \text{ or } v_{WT}\succ v_{WT,cut-out}\\ P_r\times\dfrac{v_{WT}^{3}-v_{WT,cut-in}^{3}}{v_{WT,rated}^{3}-v_{WT,cut-in}^{3}} & \text{if } v_{WT,cut-in}\le v_{WT}\le v_{WT,rated}\\ P_r & \text{if } v_{WT,rated}\le v_{WT}\le v_{WT,cut-out}\end{cases} \tag{9}$$

In Eq. (9), P_r and P_{WT} shows the output power at the rated speed and output power of the WT, respectively. v_{WT}, $v_{WT,cut-in}$, $v_{WT,cut-out}$ and $v_{WT,rated}$ are the wind speed, cut-in speed, cut-out speed and rated speed of WT, respectively.

2- 2- 3- BESS modeling

The energy storage system is specified by its energy capacity, charging power capacity, discharging power capacity, charging efficiency, and discharging efficiency. Equations (10)-(12) show the dependency between the storage content (S) and the power flow in/out of the storage (P_s) [59].

$$S(t+1)=\begin{cases}S(t)-\dfrac{1}{\eta_d}P_s(t)\Delta t; & P_s(t)\ge 0\\ S(t)-\eta_c P_s(t)\Delta t; & P_s(t)\prec 0\end{cases} \tag{10}$$

$$P_s^{\min}\le P_s(t)\le P_s^{\max} \tag{11}$$

$$S^{\min}\le S(t)\le S^{\max} \tag{12}$$

where η_c and η_d represent the charging efficiency and discharging efficiency, respectively. The electricity storage round-trip efficiency is according to Eq. (13) [59].

$$\eta_s=\eta_c.\eta_d \tag{13}$$

3- Robust optimization for uncertainty modeling

For the microgrid model to be more accurate, uncertainties in the produced power of DG units (such as WT and PV) must be considered. Uncertainty in WT output power is due to variable wind speed and uncertainty in PV output power is due to variable solar radiation. In most studies, the beta probability distribution function is generally chosen as a suitable model for expressing the hourly behavior of solar radiation. The Weibull probability distribution function is commonly used to analyze wind speed data [50]. In addition, the load uncertainty resulting from the unpredictable behavior of users is another important uncertainty that must be considered. The load uncertainty is modeled using the normal probability distribution function [50].

In the RO approach, no information about the probability distribution of the uncertain parameter is needed to consider the uncertain parameter in the mathematical model [44]. Instead, an uncertain set $c\in U(c)$ is defined for the uncertain parameters in the problem. Where *U(c)* is a distance which the unknown parameter can have a value of that distance [44]. On the other hand, RO only needs information about the upper and lower limits of uncertainty [48]. The goal of RO is to achieve a solution that is optimal if the worst case is achieved for unspecified parameters [51]. Robust bi-level models are a good alternative to making decisions in uncertain conditions. In the first level of this model, the worst case is determined for unspecified variables [47]. In the second level, the objective function is optimized by specifying the worst case of the

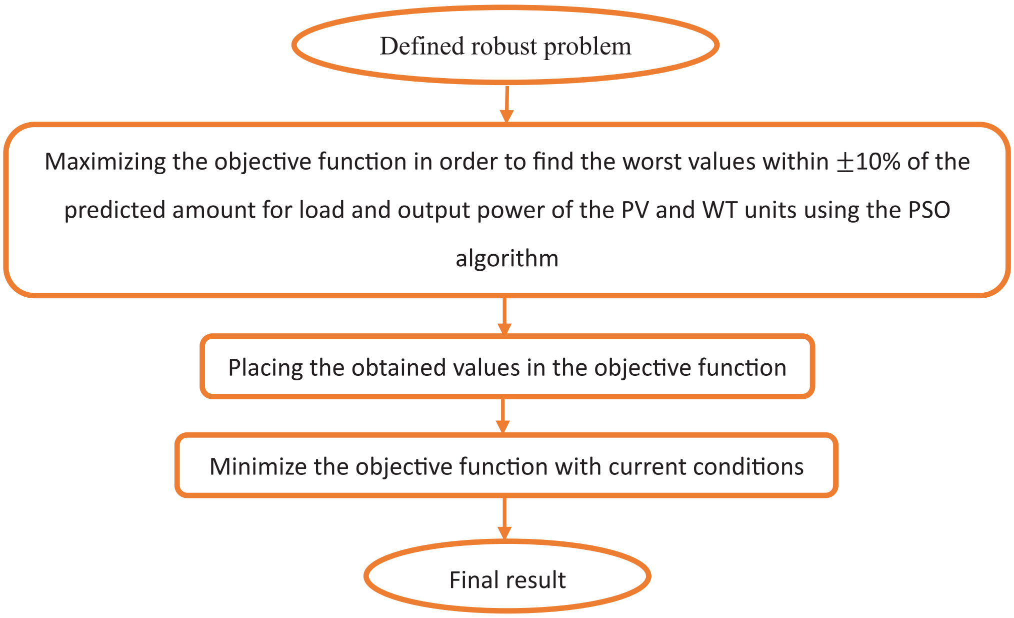


Fig. 2. The flowchart of the proposed microgrid energy management solving method

uncertain variables. In this paper, in the first level, the worst case of indeterminate parameters is obtained by maximizing the microgrid operation cost function. Then, in the second level, the objective function is optimized by considering the worst case obtained in the first level for unknown parameters. In order to achieve the best solution, levels 1 and level 2 are repeated several times. The flowchart of the proposed microgrid energy management solving method is shown in Fig. 2. There are two termination criteria:

1) Each algorithm has a maximum iteration = 150. That is, even if the algorithm reaches a constant optimum value at low iterations and there is no difference between two consecutive iterations, it continues up to 150 iterations to ensure the answer.

2) Each algorithm is run 30 times and the best one is selected as the optimal solution.

4- The optimization algorithms

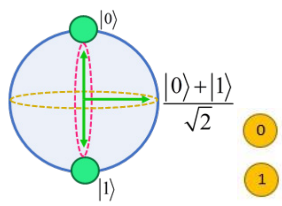
4- 1- Teaching learning-based optimization

A TLBO algorithm inspired by the traditional classroom teaching-learning approach was proposed by Rao et al. [52] in 2011. Like other nature-inspired algorithms, TLBO is a population-based method that uses a population of solutions to achieve an optimal solution [52]. This algorithm only needs common control parameters such as population size and the number of generations, but does not require algorithm-specific control parameters [53]. In order for students to master each subject in the classroom, they need to go through two steps: (a) the teacher stage; where the average grade of the class is improved by the teacher, and (b) the student stage; where students interact with each other to increase their knowledge in each subject [1]. More information about the TLBO algorithm is given in [1].

4- 2- Quantum Teaching Learning-Based Optimization algorithm

4- 2- 1- Introduction to Quantum Computational Iquantum intelligence

Similar to traditional intelligent algorithms, quantum search algorithms distinguish between population representation and fitness evaluation. But unlike traditional intelligent algorithms, they use quantum bits to represent population elements instead of binary representations. The smallest piece of information in quantum computing is named Quantum bit (Q-bit). As shown in Fig. 3, the Q-bit is either in the “1” state, in the “0” state, or in any superposition of both states, i.e., in the probabilistic linear superposition of the two states. Therefore, one of the advantages of Q-bit representation over binary representation is the improvement of population diversity [54].



(a) (b)

Fig. 3. (a) Classical bit display; (b) Q-bit display [1]

Table 1. Data of DG units and main grid [55]

Type of Source	Min. Power (kW)	Max. Power (kW)	Start-up/Shut-down Cost (€ct)	Bid (€ct/kWh)
MT	6	30	0.96	0.457
FC	3	30	1.65	0.294
PV	0	25	0	2.584
WT	0	15	0	1.073
BESS	-30	30	0	0.380
Main Grid	-30	30		

4- 2- 2- QTLBO

A quantum population consisting of P students is defined in the QTLBO algorithm. Each of these students has M subject to learn in a course [1]. The details of the QTLBO algorithm are described in [1]. The pseudo-code of the QTLBO algorithm is given in [1]

.

5- Simulation results and discussion

In the present paper, a grid-connected microgrid testing system shown in Fig. 1 is used. The data of DG units are according to Table 1 [55]. The data on the main grid market price and forecasted load for 24 hours are given in [1].

The simulations are performed using MATLAB R2020b software. The RO is used to take into account the uncertainties caused by the random behavior of PV, WT, and loads. In order to compare the optimality and convergence accuracy of TLBO, QTLBO, RCGA, and DE algorithms with each other, the results are presented all together. The population size of all algorithms is 200, and the maximum iteration is 150. The RCGA algorithm data are 4, 0.8, and 0.2 for the crossover and mutation distribution index, crossover probability, and mutation probability, respectively [1]. The DE algorithm data are 0.7 and 0.5 related to the crossover probability and scaling factor, respectively [1].

To take into account the uncertainties in the load and in the output of WT and PV, RO has been used, which is solved by the PSO algorithm. The predicted values of the load, WT, and PV power are denoted by $\overline{P_t^{load}}$, $\overline{P_{i,t}^{WT}}$, and $\overline{P_{i,t}^{PV}}$, respectively. The predicted power of the WT is obtained by predicting the wind speed and using Eq. (9). The predicted power of the PV is obtained by predicting the amount of solar radiation and using Eq. (7). Eq. (14) gives the set of intervals for uncertainties.

$$
\begin{aligned}
&P_t^{load} \in \left[\left(1+\alpha_{l,t}^{\min}\right)\overline{P_t^{load}},\left(1+\alpha_{l,t}^{\max}\right)\overline{P_t^{load}}\right]\\
&P_{i,t}^{WT} \in \left[\left(1+\alpha_{wt,t}^{\min}\right)\overline{P_{i,t}^{WT}},\left(1+\alpha_{wt,t}^{\max}\right)\overline{P_{i,t}^{WT}}\right] \qquad (14)\\
&P_{i,t}^{PV} \in \left[\left(1+\alpha_{pv,t}^{\min}\right)\overline{P_{i,t}^{PV}},\left(1+\alpha_{pv,t}^{\max}\right)\overline{P_{i,t}^{PV}}\right]
\end{aligned}
$$

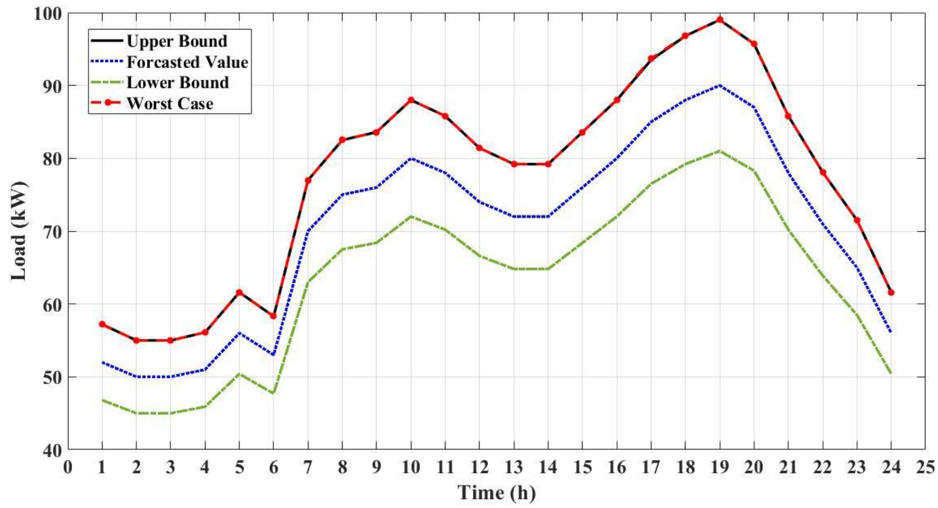
In this work, the change range of uncertainties is 10%. In order to achieve the worst case of load and output power of WT and PV within ±10% of the predicted value, the objective function introduced in Eq. (1) is maximized. After running the PSO algorithm for this problem several times, the load and the output powers of the PV and WT related to the worst case are obtained. The results for considering uncertainties using RO are shown in Table 2 and Fig. 4. As shown in Fig. 4, the worst cases are on the boundaries. After determining the worst case for uncertain parameters (Load, WT and PV output power), the objective function must be minimized to determine the final optimal values of the microgrid energy management problem. The QTLBO, TLBO, DE, and RCGA algorithms were used to minimize the objective function. Each of these algorithms was run 30 times. The best result of 30 runs was selected as the final solution.

The best results of the QTLBO algorithm are given in Table 3. The values of the load, PV, and WT columns in Table 3 represent the worst-case values of load, PV, and WT power outputs; which are obtained using RO. The negative sign in the grid power column means selling electricity to the main grid, and the positive sign in the same column means buying electricity from the main grid. A negative sign in the cost column means profit and a positive sign in the same column means expenses. A negative sign in the BESS column means that the BESS is charged and a positive sign in that column means it is discharged. Table 3 indicates that the grid power is negative during hours when the price of electricity is high. This means that microgrid energy management is done correctly using the QTLBO algorithm; because it is cost-effective to sell power to the main grid during hours with high electricity prices. Also, in the hours when the price of electricity is at its highest value, it is profitable to sell additional power to the main grid.

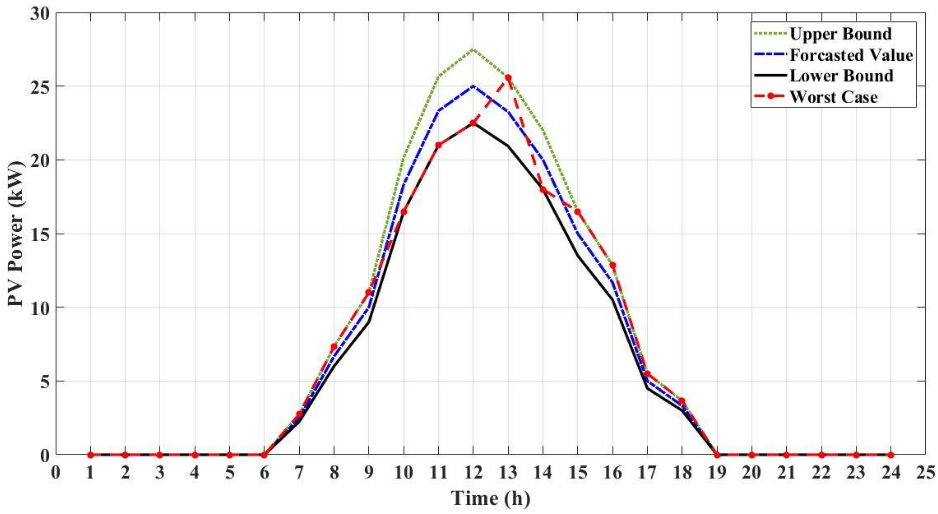
As shown in Fig. 5, the best results (costs) of the QTLBO, TLBO, DE, and RCGA are 527.3476 €ct, 541.8142 €ct, 558.4033 €ct, and 563.9243 €ct, respectively. According to Fig. 5, it can be seen that the QTLBO algorithm has a better response than the TLBO, DE, and RCGA algorithms. In addition, this algorithm converges to the optimal value faster than other algorithms.

Table 2. The predicted values for PV and WT power, and the resulting values of RO

Time (h)	Load		PV		WT	
	Predicted Value (kW) [1]	RO Result (kW)	Predicted Value (kW) [56]	RO Result (kW)	Predicted Value (kW) [56]	RO Result (kW)
1	52	57.2	0	0	4.875	5.3625
2	50	55	0	0	4.5	4.95
3	50	55	0	0	4.125	4.5375
4	51	56.1	0	0	4.125	4.5375
5	56	61.6	0	0	3.75	4.125
6	53	58.3	0	0	3.375	3.7125
7	70	77	2.5	2.75	3.75	4.125
8	75	82.5	6.675	7.3425	6	6.6
9	76	83.6	10	11	7.5	6.75
10	80	88	18.32	16.4925	10.5	9.45
11	78	85.8	23.32	20.9925	12	10.8
12	74	81.4	25	22.5	12	10.8
13	72	79.2	23.25	25.5750	13.5	12.15
14	72	79.2	20	18	14.25	12.825
15	76	83.6	15	16.5	15	13.5
16	80	88	11.67	12.8425	14.25	12.825
17	85	93.7	5	5.5	13.12	14.4375
18	88	96.8	3.325	3.6575	12	13.2
19	90	99	0	0	9.75	10.725
20	87	95.7	0	0	6.75	7.425
21	78	85.8	0	0	6.375	5.7375
22	71	78.1	0	0	4.875	5.3625
23	65	71.5	0	0	4.125	4.5375
24	56	61.6	0	0	3.375	3.7125



(a)



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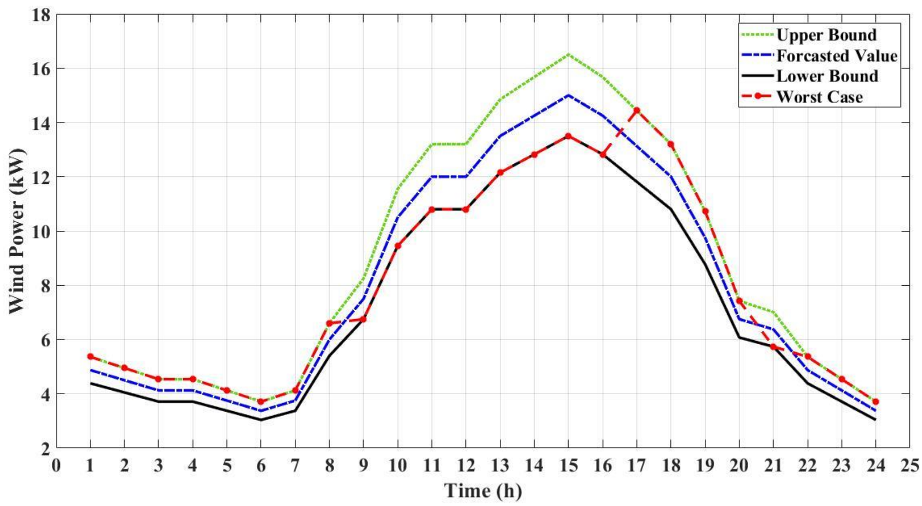


(c)

Fig. 4. Results for considering uncertainties with the RO: (a) Load; (b) PV power; and (c) WT power

Table 3. The results of the QTLBO algorithm

Time (h)	P_{MT}	P_{pv}	P_{WT}	P_{FC}	P_{BESS}	P_{grid}	P_{load}	Cost (€ct)
1	6	0	5.3625	30	-14.1625	30	57.2	21.4442
2	6	0	4.95	30	-15.95	30	55	16.5124
3	6	0	4.5375	30	-15.5375	30	55	14.7265
4	6	0	4.5375	30	-14.4375	30	56.1	14.5445
5	6	0	4.125	30	-8.5250	30	61.6	16.3486
6	6	0	3.7125	30	15.5875	30	58.3	17.2088
7	6	2.75	4.125	30	4.1250	30	77	31.5616
8	6	7.3425	6.6	30	2.5575	30	82.5	49.9887
9	30	11	6.75	30	30	-24.15	83.6	33.3717
10	30	16.4925	9.45	30	30	-27.9425	88	-25.0835
11	30	20.9925	10.8	30	24.0075	-30	85.8	-22.5141
12	30	22.5	10.8	30	18.1	-30	81.4	-20.8636
13	30	25.5750	12.15	30	11.475	-30	79.2	61.0133
14	30	18	12.825	30	18.375	-30	79.2	-30.2143
15	30	16.5	13.5	30	23.6	-30	83.6	28.6195
16	30	12.8425	12.825	30	30	-27.6675	88	26.9246
17	30	5.5	14.4375	30	29.7278	-15.9653	93.7	53.9508
18	6	3.6575	13.2	30	30	13.9425	96.8	52.2930
19	6	0	10.725	30	22.275	30	99	42.0344
20	6	0	7.425	30	30	22.2750	95.7	40.5073
21	29.8286	0	5.7375	30	30	-9.7661	85.8	28.5817
22	30	0	5.3625	30	30	-17.2625	78.1	30.3622
23	6	0	4.5375	30	0.9625	30	71.5	25.7965
24	6	0	3.7125	30	-8.1125	30	61.6	20.2628
							Total Cost (€ct)	527.3476

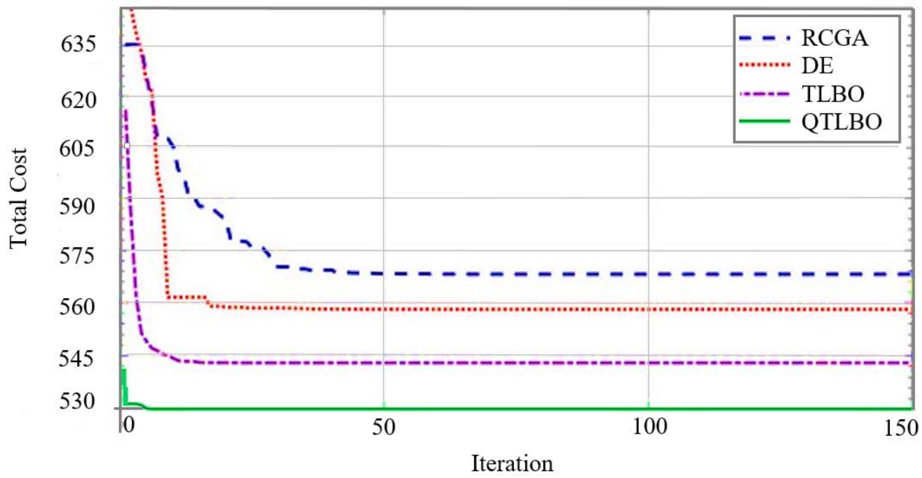
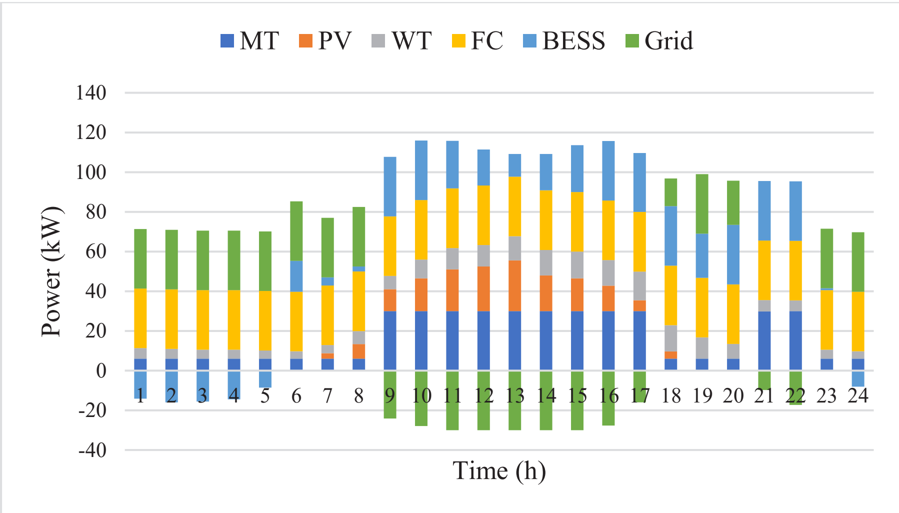
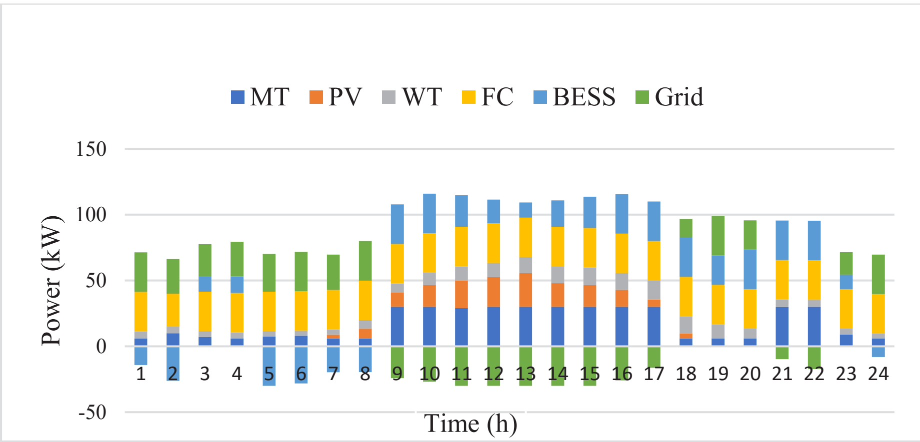


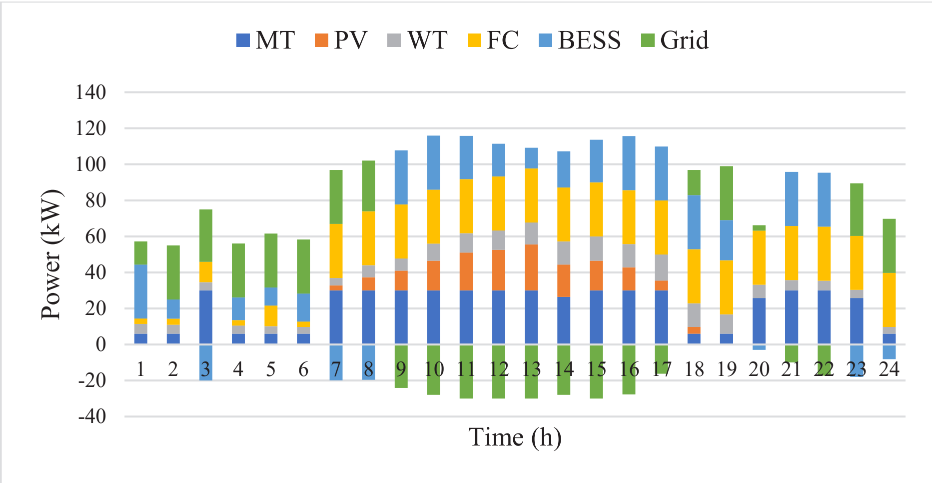
Fig. 5. Comparison of cost function curves obtained from different algorithms



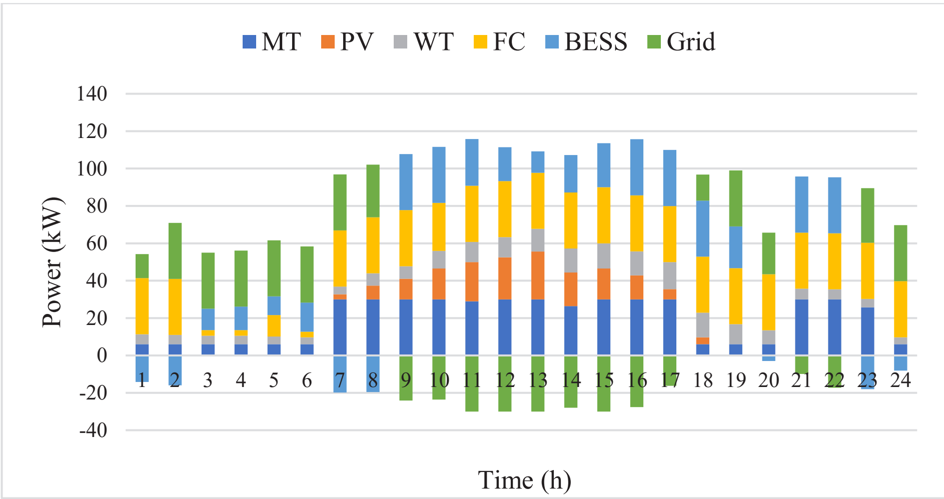
(a)



(b)



(c)

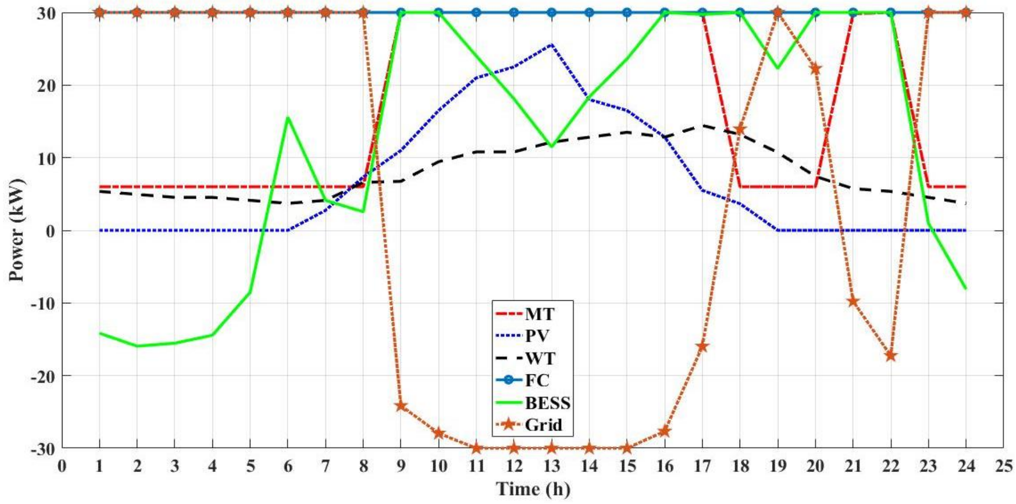


(d)

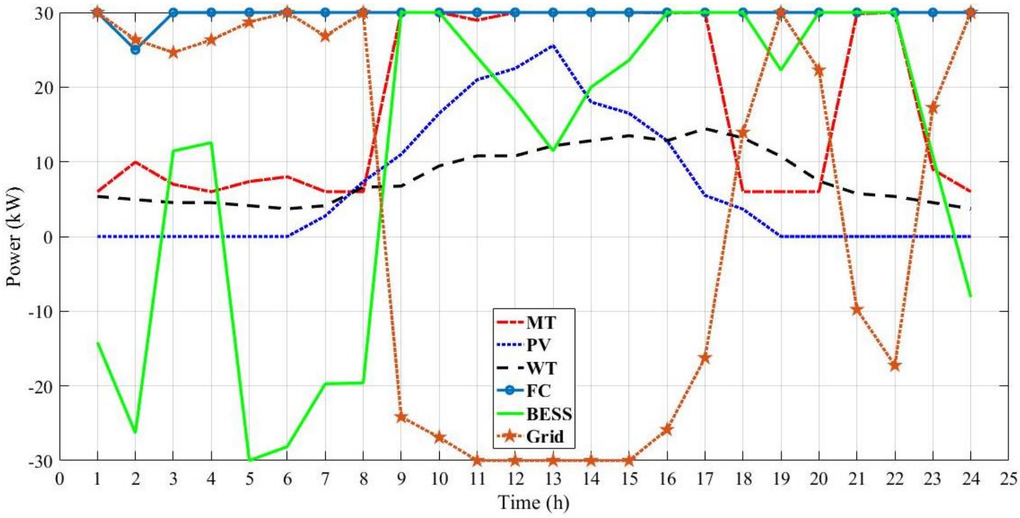
Fig. 7 Production of microgrid's DERs: (a) using QTLBO; (b) using TLBO; (c) using DE; (d) using RCGA

Fig. 6 shows the QTLBO algorithm result versus the number of runs. As can be seen in Fig. 6, the best and the worst results of the QTLBO algorithm in 30 runs are 527.3476 €ct and 541.3586 €ct, respectively. The worst result is 2.66% higher than the best result. It is worth noting that the worst result of the QTLBO algorithms in 30 runs is better than the best results of other algorithms. Also from Fig. 6, the results of 19 out of 30 runs appear in the first quarter where the worst result is only 0.61% higher than the best result. Thus, with a probability of 63.3%, a solution will be reached in the first run that is very close to the lowest operating cost obtained.

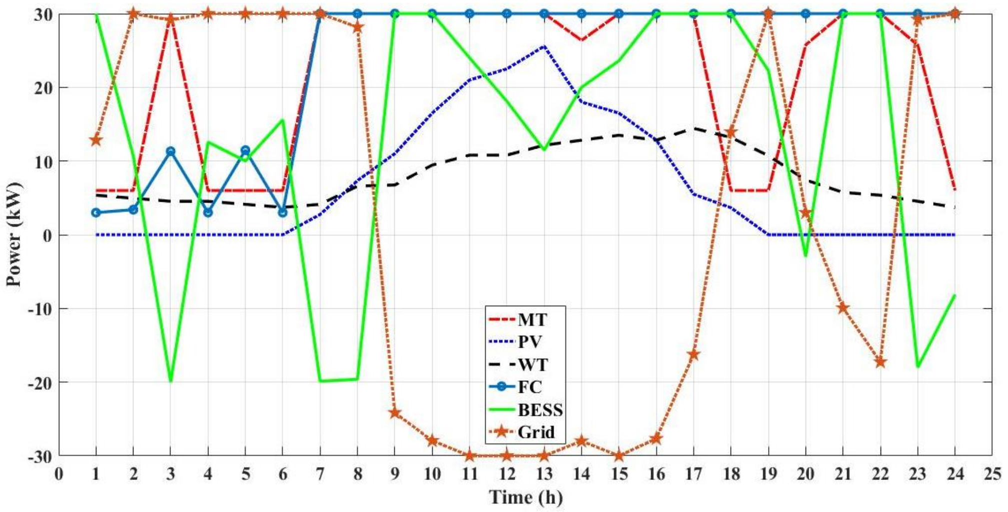
Fig. 7 (a) displays the hourly production of the microgrid's DERs using the QTLBO. Fig. 7 (b), Fig. 7 (c) and Fig. 7 (d) display the hourly production of microgrid's DERs using the TLBO, DE, and RCGA algorithms, respectively. The hourly powers of microgrid sources obtained using the QTLBO are shown in Fig. 8 (a). The hourly powers of microgrid sources obtained using the TLBO, DE, and RCGA algorithms are shown in Fig. 8 (b), Fig. 8 (c), and Fig. 8 (d), respectively. Fig. 7 and Fig. 8 show the value of power generation/consumption of each source in each hour. As can be seen in Fig. 7 and Fig. 8, the pattern of power changes of various sources is approximately the same for all four algorithms.


Power (kW)
Time (h)
MT
PV
WT
FC
BESS
Grid

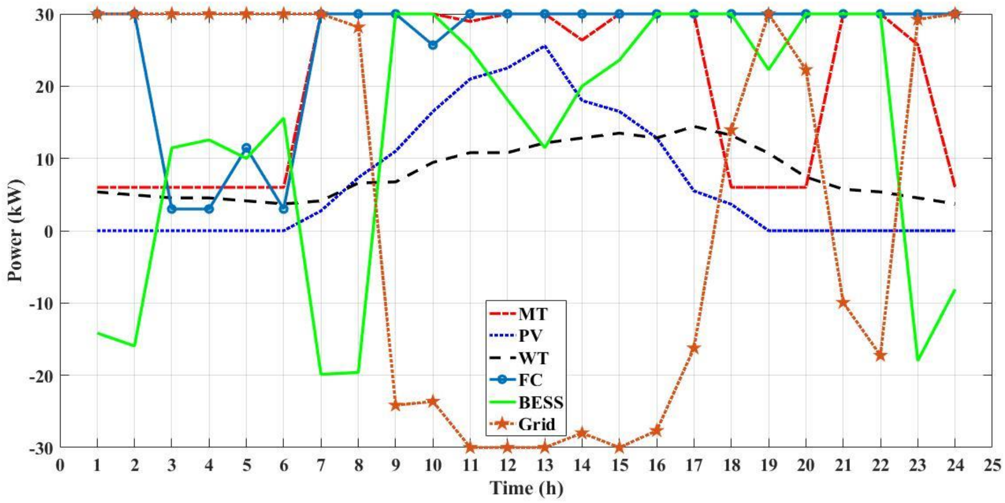
(a)


Power (kW)
Time (h)
MT
PV
WT
FC
BESS
Grid

(b)


Power (kW)
Time (h)
MT
PV
WT
FC
BESS
Grid

(c)



(d)

Fig. 8 Hourly powers of microgrid sources: (a) using QTLBO; (b) using TLBO; (c) using DE; (d) using RCGA

6- Conclusion

In this paper, a grid-connected microgrid consisting of various DG sources and a BESS is considered. The QTLBO algorithm is used to solve the problem of optimal microgrid energy management. Uncertainty in the load, WT power, and PV power are modeled using the RO-based method. This problem is formulated as a bi-level problem and a repetitive bi-level approach is used to solve it. It is shown that the worst case is placed on the boundaries of uncertain parameters. The use of quantum versions of heuristic algorithms (including TLBO), has improved their performance. Simulation results show that QTLBO is much more efficient than TLBO, DE, and RCGA since it reaches a more optimal value than the other algorithms and converges to its optimal value faster. In addition, the simulation results demonstrate that with a probability of 63.3%, the QTLBO algorithm in the first run achieves a solution that is very near to the most optimal result obtained. The presented results also show when the price of electricity is high, the flow of power is from microgrid to the main grid, as expected.

Competing Interests

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Nomenclature

Indices and sets

X	Set of decision variables
t	Time [h]
T	Time horizon [24 h]
i	Index of DGs
j	Index of BESSs
l	Index of loads
k	Index of DGs with uncertainty

Parameters

$B^t_{DG_i}$	Price of i^{th} DG unit at time t for $P^t_{DG_i}$ [€ct /kWh]
$B^t_{BESS_j}$	Price of j^{th} BESS unit at time t for $P^t_{ES_j}$ [€ct /kWh]
B^t_{grid}	Market price at time t for P^t_{grid} [€ct /kWh]
S_{DG_i}	On/off cost of i^{th} DG unit [€ct]
S_{BESS_j}	On/off cost of j^{th} BESS unit [€ct]
$P^t_{DG_i,\min}$	Min. output power of i^{th} DG unit at time t [kW]
$P^t_{DG_i,\max}$	Max. output power of i^{th} DG unit at time t [kW]
$P^t_{BESS_j,\min}$	Min. output power of j^{th} BESS unit at time t [kW]
$P^t_{BESS_j,\max}$	Max. output power of j^{th} BESS unit at time t [kW]
$P^t_{grid,\min}$	Min. output power of main grid at time t [kW]
$P^t_{grid,\max}$	Max. output power of main grid at time t [kW]
NG	Num. of DG units
NS	Num. of BESS units
ND	Num. of loads
DR_{MT}	Min. ramp rate of microturbine
UR_{MT}	Max. ramp rate of microturbine
λ_{pen}	Penalty factor

Variables

u^t_i	On/off state of i^{th} DG unit at time t
v^t_j	On/off state of j^{th} BESS unit at time t
p^t_{grid}	Power of main grid at time t [kW]
$P^t_{DG_i}$	Output power of i^{th} DG unit at time t [kW]

$P^{t}_{BESS_j}$ Output power of j^{th} BESS unit at time t [kW]

P^{t}_{MT} Output power of microturbine at time t [kW]

P^{t-1}_{MT} Output power of microturbine at time t-1 [kW]

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