Robust Energy Management of a Microgrid with Uncertain Price, Renewable Generation, and Load using Taguchi's Orthogonal Array Method

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Energy management system in a microgrid with uncertainties in load, renewable generation and market price is critical for stable operation of the microgrid. Scenario-based robust energy management exploiting upper and lower bounds is used to deal with the uncertainties. Taguchi's orthogonal array method is used to reduce the large number of scenarios, considering all the possible combinations of max and min values of loads and renewable generations. In this study, uncertainty of market price is handled by robust optimization method, and worst case scenario with the maximum total cost is defined as the output result. Furthermore, demand response program is also considered for the flexible loads, which help the microgrid to operate robustly with a lower cost, in the presence of the uncertainties. In this study, two cases with typical microgrids are considered to evaluate the effectiveness of the proposed method, and GAMS tool is used for implementation of simulations. Additionally, Monte Carlo simulation is applied for verifying the effectiveness of the method.

keywords: *Robust energy management, Microgrid, Orthogonal array method, Uncertainty, Demand response.*

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Nomenclature

A. Indices:

g Index for each conventional generation unit.

e Index for each battery storage unit.

w Index for each wind turbine.

l Index for each load.

t Index for each time step.

B. Parameters:

$a(g), b(g)$ Cost coefficients of the conventional generation unit g.

$R_{cg}^{up}(g) / R_{cg}^{down}(g)$ Ramp up/ramp down rate limit of conventional generation unit g.

$P_{cg}^{max}(g) / P_{cg}^{min}(g)$ Maximum/minimum output power of conventional generation unit g.

$SU(g,t)$ Start-up cost of conventional generation unit g.

$SD(g,t)$ Shut-down cost of conventional generation unit g.

$M_{es}(e,t)$ Maintenance cost of the battery unit e at time t.

$P_{es}^{max}(e) / P_{es}^{min}(e)$ Maximum/minimum output power of battery unit e.

$E^{max}(e) / E^{min}(e)$ Maximum/minimum capacity of battery unit e.

$\eta^{dis}(e) / \eta^{ch}(e)$ Discharge/charge efficiency of battery unit e.

$\alpha_{pur} / \alpha_{sell}$ Price of electricity purchasing from/selling to the main grid.

R^{min} Minimum required reserve capacity.

$l_{w,t}^{max} / l_{w,t}^{min}$ Upper/lower bound of the prediction interval for output power of the wind turbine w.

$l_{l,t}^{max} / l_{l,t}^{min}$ Upper/lower bound of the uncertain variable load l.

GL Grid limit for the fluctuation of the exchange power between consecutive time periods.

T Time cycle.

C. Variables:

$P_{cg}(g,t)$ Power output of conventional generation unit g at each time t.

$P_{es}(e,t)$ Power output of battery unit e at each time t.

$P_w(w,t)$ Power output of wind turbine unit w at each time t.

$P_{mg}(t)$ Exchange power with the main grid at each time t.

$P_l(l,t)$ Load demand l at each time t.

$v(g,t)$ Status of conventional generation unit g at each time t.

$x_{pur}(t)/x_{sell}(t)$ Purchasing/selling state from/to the main grid at each time t.

$J_{mg}(t)$ Exchange cost with main grid.

D. Functions:

$C_{cg}(g,t)$ Cost of power generation from conventional generation unit g at time t ($\$/hr$).

$C_{es}(e,t)$ Cost of power generation from battery unit e at time t ($\$/hr$).

$C_{mg}(t)$ Cost of power exchange with the main grid at time t ($\$/hr$).

$R^1(t)$ Reserve power item from exchange power with the main grid at each time t.

$R^2(t)$ Reserve power item from conventional generation unit at each time t.

$R^3(t)$ Reserve power item from battery unit at each time t.

$R(t)$ Total reserve power at each time t.

1. Introduction

The microgrid is defined as a cluster of several interconnected loads and distributed energy resources which can be operated connected or disconnected from the main grid [1]. Energy management system (EMS) is responsible for operation of a microgrid in reliable, secure and economical manner in either states of grid-connected or disconnected (i.e., islanded) [2].

Energy management in either operation mode of microgrid is an indispensable topic. Optimal utilization of energy resources and economic operation of the microgrid necessitate an effective EMS [3]. High penetration of renewable energy resources and their stochastic nature challenge further investigations. The deficiencies in forecasting the wind and solar energy as well as the load demand, are the main sources of uncertainties in operation of the microgrid. Therefore, approaches in order that microgrid is operated appropriately in the presence of the uncertainties are required.

The operation cost of a microgrid includes the cost of the purchased power from the main grid, conventional generation (CG) units' fuel cost and charge of maintenance. The main objective of the EMS is minimizing the total operation cost. For problem definition, the economic dispatch model was proposed based on multiple distributed generation [4] considering the energy storage system (ESS) and the spinning reserve [5]. Multi-objective model including economic factors as well as environmental issues, was proposed in [6]. Moreover, optimal economic operation of microgrid with battery ESS was discussed in [7], based on electricity price. Some studies such as [4–7] do not take into consideration uncertainty and thus result in inaccurate optimization models.

Considering uncertainties is indispensable in EMS of microgrids [8]. Therefore, the uncertainty of renewable generation (RG) and load should be taken into account in order to provide a robust energy management scheme.

Various methods are used to deal with the uncertainties. Dispatchable CG sources can be used to handle these challenges. These methods need more CG structures and cannot guarantee an economic approach [9]. Other approaches define stochastic optimization models of the uncertain economic dispatch algorithm, which describe the uncertainty by stochastic variables [10].

Stochastic optimization technique is used to deal with energy management in a microgrid containing RG, load and ESS with uncertain electric vehicles and RG in [11]. Similarly, the adaptive optimization strategy was developed for adaptation to the uncertainty of load and electricity price [12].

The optimization problem constraints are probabilistically guaranteed in stochastic strategies. In practical applications, on the other hand, it is not accurate to use a deterministic probability curve for describing the uncertainty of stochastic parameters and their variations [8]. Furthermore, the robust optimization method [13] is an effective tool to address the bounded uncertain parameters set, in which the uncertain sets are assumed to have deterministic limits [13]. Accordingly, a robust optimization model is investigated for a microgrid and the variation in RG is described by building an uncertain set [14]. This method transforms the problem of robust optimization problem into a scenario-based deterministic problem. Scenario-based analysis is the most well-known and common approach to model the uncertainties in deterministic point of view.

One of the common ways to handle uncertainties is scenario-based programming. These scenarios are designed in a way that characterizes their stochastic features. For obtaining accuracy evaluating large number of scenarios are required. The fundamental problem here is the selection of an appropriate method to reduce the large number of scenarios to a specific group of characterized tests. Numerous techniques for scenario-reduction are applied to power systems and market [15]; such as worst-case reduction method based on extreme scenario set [16], linear programming by interval optimization [17], backward-forward technique and scenario tree construction [18], to name but a few. Model predictive control for robust EMS of a microgrid is proposed in [19]. Fuzzy prediction interval model for determining upper and lower bounds of wind generation is used for finding worst-case and best-case results. Convex sum of the obtained results are final robust decisions.

In [20] two-stage EMS in networked microgrids with high penetration of RG is proposed in which energy sources are scheduled in day-ahead and they are adjusted in real-time. The uncertainties of RG, load and price are dealt with in the first stage and imbalance is adjusted in real-time. In [21] uncertainties of loads and RG are considered in a microgrid and in day-ahead, robust EMS determines the baseline exchanged power with the main grid. Distributed generation, ESS and exchanged energy with the main grid are scheduled with modified EMS in the intraday stage. In the objective function of modified EMS, difference between the exchanged energy with the main grid in day-ahead and in intraday stage is penalized in order to make the least impact on the main grid. The literature review on EMSs in microgrids which regard uncertainties are presented in [22]. Robust EMS Minimizing maximum deviation of non-optimal objective function from the optimal one under all probable uncertain loads is suggested in [23]. Robust EMS for multi microgrids under uncertainty is proposed in [24]. In [25] two-stage EMS is suggested in which CG units on/off states are determined in day-ahead with robust EMS, and charge/discharge power of ESSs, CG units output and exchanged power with main grid are scheduled in real-time. In [26] methods dealing with uncertainties in power grids are reviewed. Further, application of robust method considering uncertainty of market price is studied in [26].

In [27], a two stage robust energy management system for PV prosumer microgrid is developed in which worst case realizations of PV generation and market prices are taken into account. Furthermore, online energy management system in order to reduce costs and adjust shiftable demand to the PV's output is developed. Robust EMS considering uncertainties of loads, RG and market prices using TOA method in order to find the worst-case scenario is proposed in [28].

TOA method [8] is proposed using the robust design theory [29,30], and provides an advanced tool for robust selection of the testing scenarios. The method is based on the most probable scenarios; the parameters' values which are highly probable to occur, are assigned by the uncertain factors. Corresponding deterministic approaches are employed to describe the uncertainty, by selecting the testing scenarios and analysis. TOA method selects the minimum required number of the scenarios that provide equivalent statistical information related to the uncertainty factors set. This method provides improved ability in optimal selection of descriptive scenarios in order to characterize all the possible combinations [30] for linear model as well as quadratic optimization [31]. TOA robust scheme significantly reduces the number of testing scenarios and the computation effort compared to Monte Carlo simulation, while it yields comparable accuracy in the results.

This study is the extended version of the previous work [32]. In this paper, TOA testing method which takes into account the worst amount of uncertain variables (i.e. RG, and load) is used to develop robust energy management following [14, 33]. Furthermore, robust optimization method is exploited to handle the uncertainties of purchase and sell prices. CG, RG, battery ESS, and controllable loads which are able to shift their demands according to the received signals from EMS are present in the microgrid. Controllable loads can increase the flexibility of the grid. Exchange power with the main grid can provide benefits for microgrids [34, 35]. Therefore, the largest exchanged power with the main grid considering worst amount of uncertainties is an important factor for the robust energy management of microgrids. EMS for a microgrid optimizes cost function of microgrid including CG, ESS, and purchasing power from main grid costs. Robust energy management ensures the desired performance when the highest degree of uncertainty occurs [36]. Robust design of TOA scenarios with maximum and minimum levels is suitable method for robust energy management. TOA scenarios are determined using four characteristics named scenarios, variables, levels and strength. Strength parameter of the chosen TOA declares the rate of the possible uncertain variables combinations. Higher strength means stronger TOA which contains large number of uncertain variables' combinations. consequently, more number of scenarios are required for satisfying strength feature (the most significant characteristic) of the TOA. The worst-case scenario with the maximum total cost is considered for developing the robust energy management. EMS for the microgrid follows this scenario's results.

- In this work the robust energy management in a microgrid consisting of RG units (wind turbine and PV), CG, ESS and flexible loads is considered regarding the worst case of total costs. While, in [8] worst case scenario with regard to the cost of exchanged power with the main grid is considered. It is shown that by considering DR program total cost is reduced, although the cost of exchanged power with the main grid is increased in comparison to its counterpart without DR. It means that worst-cases with regard to exchange cost and total costs are not the same. Considering worst-case of exchange cost does not necessarily address the overall worst-case of operation costs.

- In comparison to other works [8], this work considers the flexible loads and uncertainties of market prices. Therefore, the loads can be shifted in time in order to gain benefits.

- For validation the feasibility of the proposed method, Monte Carlo simulations are performed which are not dealt with in [32].

Remainder of this study is organized as follows: Section 2 models constraints and cost function of different parts of the considered microgrid. In Section 3, robust energy management method considering price, load and RG uncertainties using TOA testing method is described. Results of the study in the case studies are provided in Section 4. Finally, conclusions are declared in Section 5.

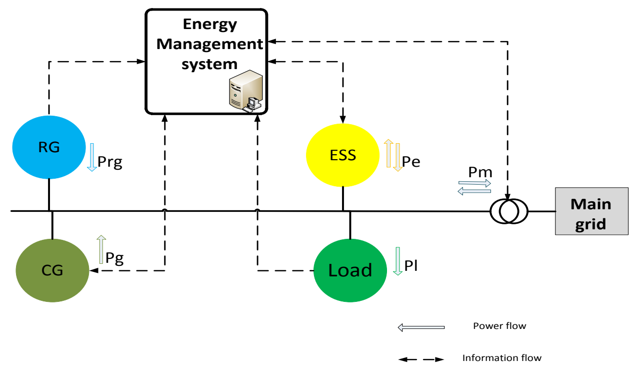

Fig. 1. Typical microgrid.

2. Microgrid modeling

The grid-connected microgrid with RG, CG, ESS, and flexible and constant loads which exchanges power with the main grid is modeled in this Section. Models of the CG units, ESS, exchange power with the main grid including their cost functions and constraints are defined. Objective function of the proposed robust EMS method is minimizing the operation costs. Studied system is depicted in Fig. 1 as [14]. The communication between the EMS and RG, load and the main grid is directed to receive the measurements. Besides, the connection with ESS and CGs should be bi-directional in order to communicate the control decisions by the EMS. The measurements and control decisions data flow in the communication system of microgrid are shown by information flow in Fig. 1.

A. Conventional generation

Part of electrical loads are provided by CGs in microgrids (e.g. diesel generators, micro turbines). In contrast to renewable energy, CG has fuel cost. Fuel cost is defined as quadratic or linear function of fuel. In this paper, fuel cost of CG is modeled as [37]

$$\begin{aligned} C_{cg}(g,t) =& a(g)v(g,t) + b(g)v(g,t)P_{cg}(g,t) \\ &+ \max(0, v(g,t) - v(g,t-1))SU(g,t) \\ &+ \max(0, v(g,t-1) - v(g,t))SD(g,t) \end{aligned} \quad \textbf{(1)}$$

where v is a binary variable, $v = 1$ if CG in on at time t, and $v = 0$ otherwise; SU and SD are the startup and shutdown cost, respectively; a and b are positive constants; and P_{cg} is the generated active power. CGs' generated power are limited by their capacity using Eq. (2). The ramp up/down of the generated powers for consequent time intervals are also limited by Eq. (3) and Eq. (4).

$$P_{cg}^{min}(g)v(g,t) \leq P_{cg}(g,t) \leq P_{cg}^{max}(g)v(g,t) \quad \textbf{(2)}$$

$$P_{cg}(g,t) - P_{cg}(g,t-1) \leq R_{cg}^{up}(g) \tag{3}$$

$$P_{cg}(g,t-1) - P_{cg}(g,t) \leq R_{cg}^{down}(g) \tag{4}$$

B. Energy storage

The battery ESS maintenance cost is [8]

$$M_{es}(e,t)|P_{es}(e,t)| \tag{5}$$

The Eq. (5) causes the problem to be non-smooth due to the absolute term. Therefore, minimizing the battery cost function Eq. (5) is modeled as Eq. (6)-Eq. (9) for linear programming [38]. The considered cost function is declared as

$$\min C_{es}(e,t) = M_{es}(e,t)y(e,t) \tag{6}$$

s.t.

$$P_{es}(e,t) \leq y(e,t) \tag{7}$$

$$-P_{es}(e,t) \leq y(e,t) \tag{8}$$

$$y(e,t) \geq 0 \tag{9}$$

A positive and a negative $P_{es}(e,t)$ represents charging and discharging modes, respectively. Battery cannot charge and discharge simultaneously and this is ensured by positive and negative values of $P_{es}(es,t)$ in charge and discharge mode, respectively. Battery's energy level is dependent on the power calculated as

$$E(e,t) = E(e,t-1) + P_{es}(e,t) \tag{10}$$

where $E(e,t)$ declares the energy state of the battery. $E(e,t)$ is limited by the capacity of the battery, as:

$$E^{min}(e) \leq E(e,t) \leq E^{max}(e) \tag{11}$$

where $E^{min}(e)$ and $E^{max}(e)$ are the minimum and maximum limits of the battery's energy. The output power of the ESS is limited by:

$$P_{es}^{min}(e) \leq P_{es}(e,t) \leq P_{es}^{max}(e) \tag{12}$$

where $P_{es}^{min}(e)$ and $P_{es}^{max}(e)$ are the minimum and maximum output of the battery. Charging and discharging power of battery should satisfy the following constraint:

$$-\eta^{dis}(e)(E(e,t-1) - E^{min}(e)) \leq P_{es}(e,t) \leq \frac{1}{\eta^{ch}(e)}(E^{max}(e) - E(e,t-1)) \tag{13}$$

where η^{ch} and η^{dis} declares charge and discharge limitation ratio of the battery, respectively. Initial and final energy of ESS are also considered the same as

$$E(e,0) = E(e,T) \tag{14}$$

where $E(e,0)$ and $E(e,T)$ are the initial and the final stored energy of the battery. T declares the time cycle for energy management.

C. The exchanged power with the main grid

Energy deficits is compensated by importing power from the main grid. Besides, monetary benefits are achieved in the case of selling energy to the main grid. In this study, different purchasing and selling prices are considered. Generally, selling price is lower than the purchase [8]. The cost of the exchanged power is defined as

$$C_{mg}(t) = P_{mg}(t)(\alpha_{pur}(t)x_{pur}(t) + \alpha_{sell}(t)x_{sell}(t)) \tag{15}$$

where x_{pur} and x_{sell} show the state of purchasing from and selling to the main grid, respectively. Active mode of each state is 1, otherwise 0. In Eq. (15), α_{pur} and α_{sell} show the purchase and sell prices. When the microgrid purchases power from the main grid, then $P_{mg}(t)$ is positive. Microgrid can purchase from or sell to the main grid at each time interval, it is not possible to buy and sell simultaneously. Therefore, the states of exchanged power with the main grid are limited as

$$0 \leq x_{pur}(t) + x_{sell}(t) \leq 1 \tag{16}$$

This constraint shows that only one state is active at each time.

The exchanged power between main grid and microgrid is limited by the following constraint:

$$P_{mg}^{min}x_{sell}(t) \leq P_{mg}(t) \leq P_{mg}^{max}x_{pur}(t) \tag{17}$$

When the microgrid sells power to the main grid, $x_{sell}(t)$ is 1 and $x_{pur}(t)$ is 0. In this case, P_{mg}^{min} is negative and thus $P_{mg}(t)$ has negative value. On the other hand when the microgrid purchases power from the main grid, $x_{pur}(t)$ is 1 and $x_{sell}(t)$ is 0. As P_{mg}^{max} is positive; thus, $P_{mg}(t)$ has positive value.

The power exchange with the main grid between time intervals is limited by the value based on the capacity of the microgrid (i.e. GL) as

$$-GL \leq P_{mg}(t) - P_{mg}(t-1) \leq GL \tag{18}$$

D. Demand response program

In this paper, it is assumed that all loads in the microgrid are controllable. System operator is allowed to shift loads. Hence, loads are shifted when RG is low and exchange prices are high, and the reduced load is shifted to the time with high RG and lower prices. Loads can fluctuate in the defined range of variations, as

$$Load(l,t)(1-\alpha) \leq P_l(l,t) \leq Load(l,t)(1+\alpha) \tag{19}$$

where the parameter α is the allowed percentage for variation of loads. $Load(l,t)$ is the predicted load should be provided at each time. $P_l(l,t)$ declares provided load after applying the demand response program. The whole requested load in the scheduling time cycle must be supplied up to end of the day. As a result, any reduction of demand is followed by increment of energy at other time intervals. Consequently, energy is constant in the considered time interval.

$$\sum_{t=1}^{T} Load(l,t) = \sum_{t=1}^{T} P_l(l,t) \tag{20}$$

Constraint Eq. (20) declares that the whole predicted load should be satisfied in the scheduling time cycle.

E. Spinning reserve

One of the resources used to cover the sudden increase in demand, rapid reduction of RG, or unplanned generation outage is spinning reserve. Reserve is supplied by generation units which can ramp up to meet the demand and is synchronized to the system [39]. It is noted that total reserve (i.e. $R(t)$) is composed of three distinct parts as $R^1(t)$-$R^3(t)$ defined in Eq. (22), Eq. (23), and Eq. (24). $R^1(t)$, $R^2(t)$, and $R^3(t)$ are the reserve power items from exchanged power with the main grid, conventional generation unit, and the battery unit, respectively. The total reserve should satisfy the minimum constraint Eq. (25) to ensure safe and secure operation of microgrid.

$$R(t) = R^1(t) + R^2(t) + R^3(t) \tag{21}$$

where $R^1(t)$, $R^2(t)$, $R^3(t)$ are

$$R^1(t) = P_{mg}^{max} - P_{mg}(t) \tag{22}$$

$$R^2(t) = \sum_{g=1}^{G} min[R_g^{up}, P_{cg}^{max}(g) - P_{cg}(g,t)] \tag{23}$$

$$\begin{aligned} R^3(t) = \sum_{e=1}^{E} min[&P_{es}(e,t) - P_{es}^{min}(e), \\ &\eta_e^{dis}(E(e,t) - E^{min}(e))] \end{aligned} \tag{24}$$

Minimum reserve power at each time interval (i.e. $R^{min}(t)$) is based on the capacity of the microgrid as shown in constraint Eq. (25).

$$R(t) \geq R^{min}(t) \tag{25}$$

F. Active power balance

The demand is supplied by conventional and renewable resources, ESS and main grid at each time step. Power is balanced at each time step as

$$\begin{aligned} \sum_{l=1}^{L} P_l(l,t) + \sum_{e=1}^{E} P_{es}(e,t) - \sum_{w=1}^{W} P_w(w,t) \\ - \sum_{g=1}^{G} P_{cg}(g,t) - P_{mg}(t) = 0 \end{aligned} \tag{26}$$

3. Robust energy management system

In this section, first, deterministic EMS is formulated, then price uncertainty is modeled using robust optimization method. After that, TOA robust method considering load and RG is described. At last, Monte Carlo method is used in order to evaluate the robustness of the proposed method.

A. Deterministic energy management system

Minimizing the costs while maintaining power balance in the microgrid is the objective of this paper. Therefore, the proposed optimization framework for minimizing costs is:

Problem P1.

$$\min \sum_{t=1}^{T} C_d + P_{mg}(t)(\alpha_{pur} x_{pur}(t) + \alpha_{sell} x_{sell}(t)) \tag{27}$$

s.t.

$$\text{Eq. } (2) - \text{Eq. } (4), \text{Eq. } (7) - \text{Eq. } (14), \text{Eq. } (16) - \text{Eq. } (26)$$

where C_d is

$$C_d = \sum_{g=1}^{G} C_{cg}(g,t) + \sum_{e=1}^{E} C_{es}(e,t) \tag{28}$$

where $C_{cg}(g,t)$ and $C_{es}(e,t)$ are defined by Eq. (1) and Eq. (6), respectively. The cost function of Eq. (27) includes all the defined costs incurred by CG, battery and exchanged power with the main grid.

B. Robust optimization considering price uncertainties

Grid connected microgrid is operated under price uncertainties which can be handled by robust optimization. The least statistical information is required in order to implement robust optimization method, in contrast to other probabilistic methods [26]. In fact, in this method lower and upper bounds of the predicted prices are sufficient. In this method, worst-case condition is taken into account and the obtained solution is firstly feasible for any values of the uncertain parameters, secondly it is optimal for the worst-case amount of the uncertain parameters [40].

It is supposed that the maximum and minimum of the purchasing and selling prices from/to the microgrid is known. As the worst-case condition is realized in robust optimization method; therefore, maximum deviation of the prices in the worst-case conditions where purchasing price is higher than the forecasted amount and selling price is lower than the forecasted selling price is considered. As a result, the inner maximizing problem is added to the objective function [41]:

$$\begin{aligned} \max_{z_{pur}(t),\, z_{sell}(t)} \sum_{t=1}^{T} P_{mg}(t)[(\alpha_{pur}(t) + z_{pur}(t)\hat{\alpha}_{pur}(t))x_{pur}(t) \\ + (\alpha_{sell}(t) - z_{sell}(t)\hat{\alpha}_{sell}(t))x_{sell}(t)] \end{aligned} \tag{29}$$

s.t.

$$z_{pur}(t) \leq 1 \ : \ \zeta_{pur}(t) \ \forall t \tag{30}$$

$$z_{sell}(t) \leq 1 \ : \ \zeta_{sell}(t) \ \forall t \tag{31}$$

$$\sum_{t=1}^{T} (z_{pur}(t) + z_{sell}(t)) \leq \Gamma \ : \ \beta \tag{32}$$

$$z_{pur}(t), z_{sell}(t) \geq 0 \tag{33}$$

where $\zeta_{pur}(t)$, $\zeta_{sell}(t)$ and β are dual variables. $\hat{\alpha}_{pur}(t)$ and $\hat{\alpha}_{sell}(t)$ show the max and min allowed purchasing and selling prices' deviations, and Γ is called budget which declares degree of robustness that is determined by the microgrid operator. If Γ is $2T$ it means that the microgrid is robust against price fluctuation during whole scheduling interval. Otherwise, if Γ is 0, it means that no robustness is considered. $z_{pur}(t)$ and $z_{sell}(t)$ show share of budget at each time slot for purchasing and selling prices, respectively.

Dual of the problem Eq. (29)-Eq. (33) is obtained as

$$\min_{\zeta_{pur}(t),\, \zeta_{sell}(t),\, \beta} \sum_{t=1}^{T} (\zeta_{pur}(t) + \zeta_{sell}(t)) + \beta\Gamma \tag{34}$$

s.t.

$$\zeta_{pur}(t) + \beta \geq P_{mg}(t)\hat{\alpha}_{pur}(t)x_{pur}(t) \ \forall t \tag{35}$$

$$\zeta_{sell}(t) + \beta \geq -P_{mg}(t)\hat{\alpha}_{sell}(t)x_{sell}(t) \ \forall t \tag{36}$$

$$\zeta_{pur}(t),\ \zeta_{sell}(t),\ \beta \geq 0 \tag{37}$$

Obtained inner problem Eq. (34)-Eq. (37) is integrated to the upper level problem Eq. (27), so the objective in this paper is to solve the following optimization problem:

$$\min C_d + \zeta_{pur}(t) + \zeta_{sell}(t)) + \beta\Gamma$$

s.t.

$$\text{Eq. (2)} - \text{Eq. (4)}, \text{Eq. (7)} - \text{Eq. (14)}, \text{Eq. (16)} - \text{Eq. (26)},$$
$$\text{Eq. (35)} - \text{Eq. (37)}$$

C. Robust optimization considering load and renewable generation uncertainties via taguchi's orthogonal array robust design method

An advanced EMS for a microgrid requires consideration of the uncertainties caused by errors in forecasting the intermittent renewable energy resources and loads. A common approach in dealing with these uncertainties is the scenario-based scheduling methods. Probabilistic methods such as the Monte Carlo creates large number of scenarios to increase accuracy. Due to the computational burden, several methods are used to decrease the number of scenarios while keeping the accuracy. TOA testing method is used to design representative scenarios [29]. Certain scenarios of TOA are designed or selected based on number of uncertain variables [8]. Consideration of maximum and minimum limits for levels of uncertain variables makes this method suitable for robust optimization.

For systems with uncertain variables, making system less sensitive to uncertainties is necessary. Designed or selected TOA scenarios are representative of possible scenarios which makes results less sensitive to unpredicted uncertain variables fluctuations. Scenarios in each cycle of TOA method are selected based on 4 parameters [29].

In this paper, TOA scenarios are declared in the form of OA(A,B,C,D), which is a matrix with A rows and B columns. A shows the number of selected scenarios. B is the number of uncertain variables which have C levels. Levels are the possible amount of variables based on forecasted results. D is called strength and is equal to the number of columns where guaranteed to see all the possibilities of variables' combinations in an equal number of times. It means that in any selected D number of columns, different combinations of those variables occurs the same number of times. Combination of variables' levels in TOA scenarios are distributed uniformly over the space of all possible combinations. Higher strength means stronger TOA which contains more number of uncertain variables' combinations. Consequently, higher number of scenarios are required for satisfying higher strength value.

If any two columns of selected or designed TOA are exchanged or ignored, the same features are kept for the new created TOA [31]. One can realize the TOA scenarios using the design algorithm [29, 30] and from the prepared online library [42] as well. The easiest way is to choose proper one from TOA library [42]. The number of variables (i.e. B) are fixed in this library. So if the numbers of uncertain variables (i.e. number of columns) are not equal to the existed ones, one can choose the array which has more variables, according to the feature explained earlier. If the problem has 3 uncertain variables with 2 levels, OA(4,3,2,2) is the proper array can be chosen from TOA library [42] to represent the selected scenarios.

$$\text{OA(4,3,2,2)} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

D. Designed energy management of microgrid

The objective of the EMS for a microgrid is to supply the demand with minimum cost.

For making the system less sensitive and robust to unpredicted variations, robust energy management is applied. In this study, scenario-based robust energy management of the microgrid based on the largest exchange cost with the main grid and total cost is introduced. TOA testing method is used to create the most possible scenarios. According to TOA scenarios for two uncertain variables of RG and load demand, the energy management problem of the typical microgrid in Fig. 1 is designed as Eq. (38) based on the operational constraints and cost functions of all resources. Two different programmings for robust EMS which take into consideration worst-case scenarios based on largest exchange cost and total cost are explained in the following subsections.

D.1. Robust energy management based on exchange cost

In this subsection, robust programming based on the scenario of TOA with largest exchange cost is explained [8].

Problem P2.

$$\min C_d + \zeta_{pur}(t) + \zeta_{sell}(t)) + \beta\Gamma \quad \textbf{(38)}$$

s.t.

$$J^*_{mg} \geq \sum_{t=1}^{T} P_{mg}(t)((\alpha_{pur}(t) + z_{pur}(t)\hat{\alpha}_{pur}(t))x_{pur}(t)$$
$$+ (\alpha_{sell}(t) - z_{sell}(t)\hat{\alpha}_{sell}(t))x_{sell}(t)$$
$$\forall s \in S \; by \; Taguchi's \; OA \quad \textbf{(39)}$$

and

$$\text{Eq. (2)} - \text{Eq. (4)}, \text{Eq. (7)} - \text{Eq. (14)}, \text{Eq. (16)} - \text{Eq. (26)},$$
$$\text{Eq. (35)} - \text{Eq. (37)}$$

The search strategy based on TOA for energy management of the microgrid is explained below. In the following, J^*_{mg} is the exchange cost related to the worst-case scenario s^*.

- Description of input data including network data, load characteristic, RG and ESS parameters.
- Defining optimization problem.
- Making interval prediction for finding RG and load power bounds.
- Designing scenarios based on TOA with different cycles.
- Two-stage optimization based on the designed TOA scenarios.
  - **Stage I:**
    For each scenario $s = 1, 2, ..., S$
    Do optimization P2 based on sets of uncertain variables in each scenario
    update decision variables in each scenario
    Calculate exchange cost (J^s_{mg}) based on Eq. (15)
    End
  - **Stage II**: J^*_{mg}=max(J^s_{mg})
    Update s^* corresponding to J^*_{mg}
- Getting the robust results for the maximum exchanged cost while obtaining the minimum social benefit cost.
- Obtaining the robust energy management results based on the calculated optimum worst-case scenario.

D.2. Robust energy management based on total cost

In this subsection, robust programming is introduced based on the scenario of TOA with largest total cost Eq. (27).

Problem P3.

$$\min C_d + \zeta_{pur}(t) + \zeta_{sell}(t)) + \beta\Gamma$$

s.t.

$$C^* \geq C^s$$
$$\forall s \in S \text{ by } Taguchi's\ OA \tag{40}$$

and

$$\text{Eq. } (2) - \text{Eq. } (4), \text{Eq. } (7) - \text{Eq. } (14), \text{Eq. } (16) - \text{Eq. } (26),$$
$$\text{Eq. } (35) - \text{Eq. } (37)$$

where

$$C^s = \sum_{t=1}^{T} C_d + P_{mg}(t)[(\alpha_{pur}(t) + z_{pur}(t)\hat{\alpha}_{pur}(t))x_{pur}(t)$$
$$+ (\alpha_{sell}(t) - z_{sell}(t)\hat{\alpha}_{sell}(t))x_{sell}(t)]\ \forall t \tag{41}$$

where C^s is related to the total cost of the scenario s which is defined in Eq. (41). The worst-case scenario's total cost is declared by C^*.

The schematic of TOA-based robust EMS is introduced in Fig. 2. The loss of lines is ignored in this problem and is supposed that entire loads and sources are connected to the single node [8, 20]. Thus, when the number of loads and sources increases, the previous and new loads and sources are aggregated. Consequently, single load and source with different amount and capacity are present in the microgrid. Therefore, microgrid system with any number of CG, RG, ESSs and loads can be modeled as system in Fig. 1.

E. Monte Carlo simulation

The effectiveness of the method is verified by Monte Carlo simulations. For dealing with the most probable scenarios TOA approach is chosen for robust energy management. Robustness degree of the proposed method is evaluated by comparison of the TOA results with the Monte Carlo. In this study, robust energy management following the worst case of the largest total cost is explored. Obtained total costs are compared with the worst total cost of TOA method. Number of scenarios with more than TOA amount are counted for calculation of the robustness degree which is defined as

$$\gamma = \rho^*/\rho \times 100\% \tag{42}$$

where ρ is the total number of the Monte Carlo simulations. ρ^* shows the number of simulations where total cost for Monte Carlo simulations are more than the results by TOA method. γ shows the robustness degree. If the robustness degree (i.e., γ) is lower than γ^* (γ^* is the acceptable criterion), the effectiveness of the method is verified.

4. Simulation results

The proposed robust EMS is applied to two microgrid test systems. The simulation results are divided to two parts. In the first part, uncertainties of loads and RG are taken into account. Moreover, small microgrid is considered, and DR role in costs is analyzed. Furthermore, Monte Carlo simulations are carried out, and results with different deviations for RG and load are evaluated. In the second part, uncertainties of loads, RG and prices are considered, and simulation results for different values of budgets are obtained.

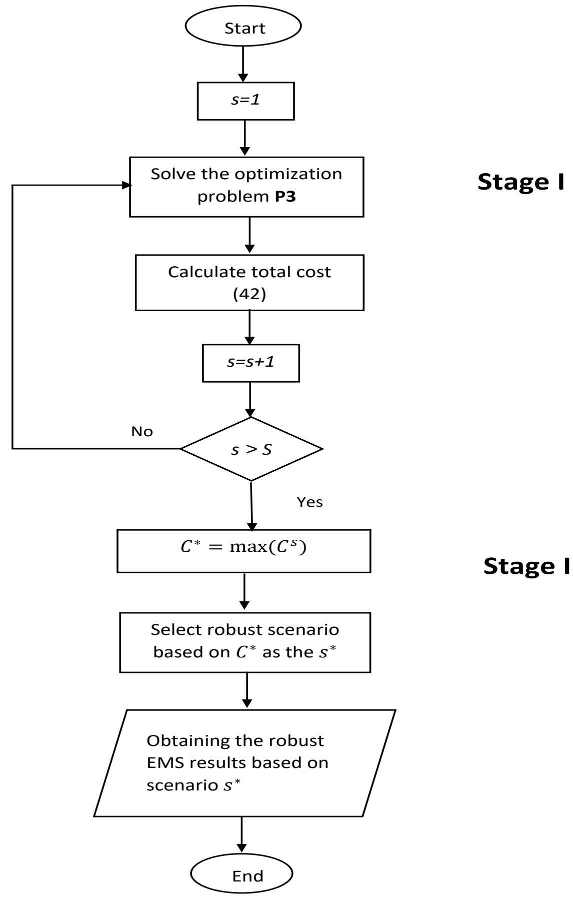

Fig. 2. The schematic of two-stage optimization based on designed TOA scenarios.

A. Case study I: robust energy management of a microgrid with toa method considering load and rg uncertainties

The microgrid characteristics are stated in the following. Three CGs are considered in the microgrid which are depicted in Fig. 1. Maximum and minimum output power, power ramp limits, cost coefficients (i.e. a and b), and start-up and shot-down costs for each unit are given in Table 1. The operational characteristics of the battery ESS, including the range of the energy level, capacity and charging/discharging efficiencies are listed in Table 2. Cost of battery maintenance M_{es} is 0.18 \$/kWh. Exchange power with the main grid limitations (i.e. P_{mg}^{max}, P_{mg}^{min}) are 30 and -30 kW, respectively. Power fluctuation limitation at each time interval (i.e. GL) is considered 10 kW.

Table 1. Parameters of the Conventional Generation Units in case I

CG	a	b	P_{cg}^{min}	P_{cg}^{max}	R^{up}/R^{down}	$SU(g)$	$SD(g)$
	\$/h	\$/kWh	kW	kW	kW/h	\$	\$
1	30	0.13	0	40	25	50	50
2	50	0.2	0	40	25	50	50

Load and output power of WT including their predicted level and upper and lower bounds, which deviates σ from the predicted values, are shown in Figs. 3 and 4. Load and output power of WT at each time is considered as an uncertain variable. Consequently, the number of uncertain variables are 48. For each variable, two levels are considered (i.e. the upper and lower bounds). Designed TOA of the library [42]

Table 2. Parameters of the Battery ESS in Case I

SoC_{min} kWh	SoC_{max} kWh	P_{es}^{min} kW	P_{es}^{max} kW	η^{dis}	η^{ch}
0	30	-20	20	0.95	0.95

are used to find the suitable TOA for the problem with 48 variables consisting of two levels. OA(96,48,2,3) is the chosen TOA for the proposed programming problem which consists of 96 scenarios. Although, 2^{48} scenarios could be selected for different combinations of two levels without TOA testing method.

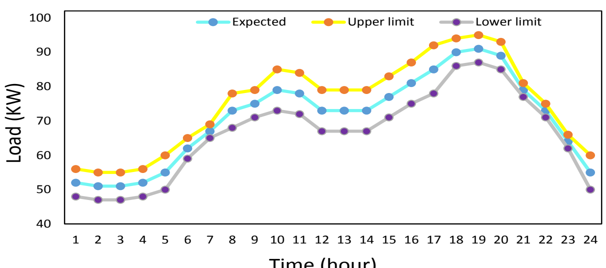

Fig. 3. Forecasted load demand and prediction interval in case I.

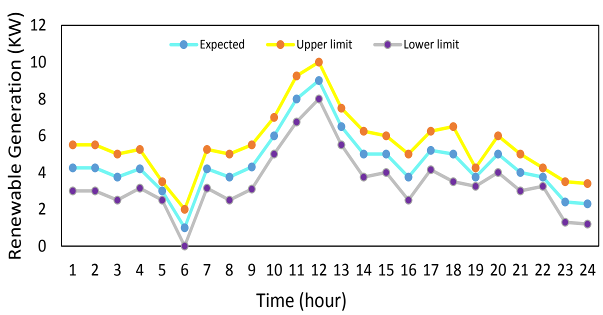

Fig. 4. Forecasted renewable power generation from the wind turbine and prediction interval in case I.

According to robust model considering extremes, four cycles are designed for TOA scenarios as shown in Table 3. Upper and lower bounds of uncertain variables are declared with the following parameters: $L_{w,t}^{min}$ and $L_{w,t}^{max}$ are limits of output power of the WT; $L_{l,t}^{min}$ and $L_{l,t}^{max}$ are the limits of the load. Four cycles can be designed containing different combinations of these limits. Totally, 384 scenarios are used in this programming.

In this study, 24 hours load demand and RG are considered as uncertain variables. Two levels are considered for each uncertain factor, taking into account the worst amounts of RG and load. The proper TOA with these properties (i.e. 48 uncertain variables with 2 levels) is chosen from the library [42]. In each scenario, 0 and 1 are considered as the lower and upper levels, respectively. Moreover, all possible combinations of the upper and lower levels are proposed using the designated TOA cycles given in Table 3. Considering chosen OA(96,48,2,3), according to the feature of TOA, which is explained in Section 3, each combination of 3 variables is repeated the same number of times in that 3 columns including the selected variables; therefore, examining the cycles 1 and 2 or 3 and 4 is sufficient. α is 20%. Therefore, loads are allowed to fluctuate in the range of 80% and 120% of considered base load in each scenario.

Table 3. Designed TOA Cycles

Cycle	Level	WT	Load
1	0	$L_{w,t}^{min}$	$L_{l,t}^{min}$
1	1	$L_{w,t}^{max}$	$L_{l,t}^{max}$
2	0	$L_{w,t}^{min}$	$L_{l,t}^{max}$
2	1	$L_{w,t}^{max}$	$L_{l,t}^{min}$
3	0	$L_{w,t}^{max}$	$L_{l,t}^{min}$
3	1	$L_{w,t}^{min}$	$L_{l,t}^{max}$
4	0	$L_{w,t}^{max}$	$L_{l,t}^{max}$
4	1	$L_{w,t}^{min}$	$L_{l,t}^{min}$

A.1. Robust energy management results with different purchase and sell prices

For showing the effectiveness of the TOA method, the proposed robust energy management of a microgrid considering load and RG uncertainties is applied to the typical microgrid shown in Fig. 1 with parameters which are declared previously. The purchase and sell prices variations in each time step are depicted in Fig. 5 ($\alpha_{sell} = 0.8\alpha_{pur}$).

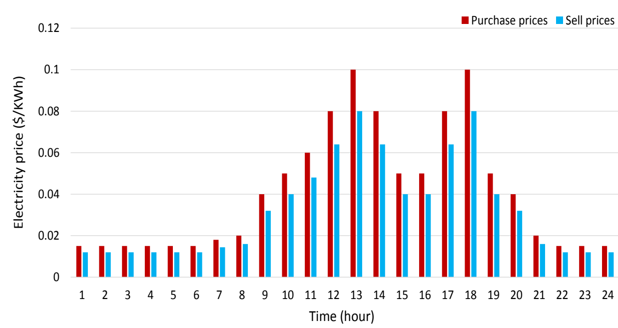

Fig. 5. Electricity price in case I.

According to Table 4 the largest total cost occur in scenario 49 of cycle 2 and scenario 1 of cycle 3. These scenarios have same results. In these scenarios the exchange cost is 285.2 $ and the total cost is 1348.9 $. As the results in Table 4 shows, the same operation costs are caused by cycles 1 and 3, it is due to the feature of TOA which is explained in Section 3. Considering chosen OA(96,48,2,3), each combination of 3 variables is repeated the same number of times in that 3 columns including the selected variables; therefore, examining the cycles 1 and 2 or 3 and 4 is sufficient.

Total cost with considering predicted amounts of load and RG in the Table 4, show that microgrid gains profits and experiences reduced costs with deployment of demand response program. It is shown in Table 4 that worst exchange cost with demand response program is higher than without demand response program. It is due to the provision of loads at different times from other sources which are cheaper than

Table 4. Comparison of the TOA-based Robust Programming Performance with and without Applying Demand Response in Case I

	With demand response program	Without demand response program
Worst-case total cost	1348.9 $ (Scen. 49 cycle 2, Scen. 1 cycle 3)	1556.5 $ (Scen. 49 cycle 2, Scen. 1 cycle 3)
Worst-case exchange cost	285.1 $ (Scen. 49 cycle 2, Scen. 1 cycle 3)	270.7 $ (Scen. 76 cycle 2, Scen. 28 cycle 3)
Expected total cost ($)	1091.2$	1326.8 $

exchanged power with the main grid in the case that flexible loads are presented.

Results for the robust EMS based on total cost are presented below. In Fig. 6 the positive value shows that load is provided in that slot because it leads to economical benefits while negative values depicts that part of load in that slot is shifted to other slots with low prices.

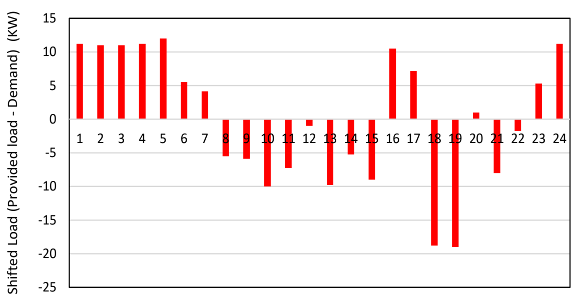

Fig. 6. Results of the demand response program in case I: the shedded and shifted loads.

The battery state in Fig. 7 shows that battery is charged at times when prices are low in the presence of demand response program and discharges the battery at times when prices are high (i.e., at hours 18, 19 and 20). On the other hand, without flexible loads the battery charges and discharges at time slots when the demand is requested and it must be provided. Therefore, charging and dischargin in inappropriate time increases operation costs

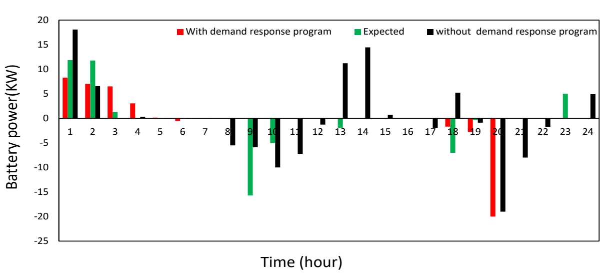

Fig. 7. Battery power for expected and worst case scenarios in case I.

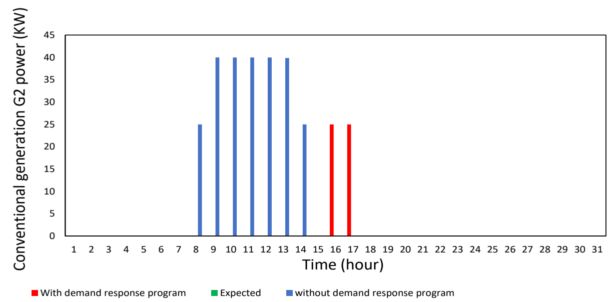

Fig. 8. Generation of CG2 for the expected and worst case scenarios in case I.

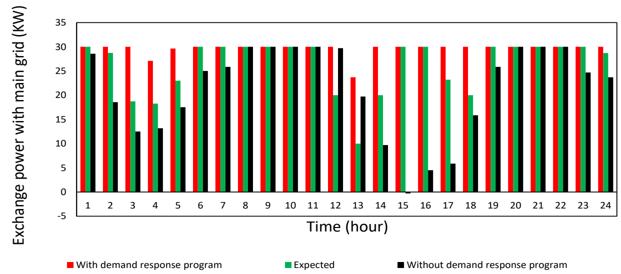

Fig. 9. The exchanged power with the main grid for the expected and the worst case scenarios in case I.

Load demand is initially provided with RG. The remainder is supplied by CG, ESS and the main grid. When purchase price is lower than CG, it is more beneficial to provide remaining loads by purchasing from the main grid after using RG. Totally it is not constructive to supply the total load using the CG units, due to its high operation costs. Although, operational constraints related to limitations of exchanged power with main grid restricts supplying whole remainder load from the main grid. The robust programming provides some load demand from CG and the remaining demand from the main grid and battery as shown in Figs. 7, 8 and 9. If demand response program is applied to the microgrid as proposed in this paper, the load is shifted; therefore, the loads are provided later at low price times without exploiting CG2 units which is costly. It is shown in Fig. 8 that CG2 is used from hour 8 to hour 14 in the case that load is inflexible, but the load is declined at times from 8 to 14 when load is flexible as shown in Fig. 6 in order to reduce costs by providing load at later times from main grid when the prices are low.

To demonstrate the advantages of applying demand response programs, results of EMS with and without applying demand response program are compared in Table 4.

A.2. Monte Carlo simulation

Monte Carlo simulations for verifying the feasibility of robust TOA-based EMS method are performed. It is considered that the distribution of load and output power of WT are normal. The number of scenarios and acceptable criterion (i.e., γ^*) are 10000 and 3%, respectively. In order to investigate the effect of the uncertainty on the TOA-based robust EMS, different values for deviation of the uncertain variables are considered. In Fig. 10(a), first the TOA scenarios for different values of σ, where σ is defined as deviation of the values of load and RG from their forecasted amounts, are selected and costs given these scenarios are obtained. Then, the number of Monte Carlo costs which are between two robust costs are calculated and is depicted in

Fig. 10(a). For example cost resulted from TOA-based robust method for 0.1σ is 1101$ and the number of Monte Carlo scenarios' costs lower than 1101$ is 73.65%. Costs resulted from TOA-based energy management system for different values of σ are compared with the Monte Carlo's resultant costs. The number of Monte Carlo's resultant costs which are lower than the costs obtained from various values of σ are calculated in Fig. 10(a). Operation costs are obtained considering different fractions of σ where $\hat{\sigma}$ shows the fraction of deviation with respect to σ. Results in Fig. 10(a) show that for deviation of σ the robustness degree is 0% which is lower than acceptable criterion 3%.

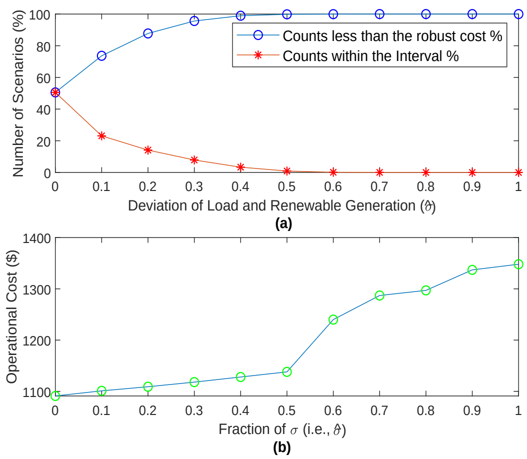

Fig. 10. Monte Carlo simulation results for different values of σ; (a)Percentage of costs obtained by Monte Carlo simulation compared to costs resulted from TOA-based method considering various values of σ, (b) Costs resulted from TOA-based energy management system for different values of σ.

Costs obtained from TOA-based energy management system applying different values of σ are shown in Fig. 10(b). Fig. 10(a) depicts that the preferred robustness degree is also attainable for the energy management system with deviation of 0.4σ which poses less cost as depicted in Fig. 10(b), while higher σs cause more costs. Thus, according to the results, the desired robustness is achievable with the lower cost.

B. Case study II: robust energy management of a microgrid considering load, rg and price uncertainties

The microgrid used in the Case study II is considered similar to the system in [43]. The microgrid consists of 7 CG and 2 battery ESS, and it can exchange power with main grid. Characteristics of the CG units and battery ESSs are declared in Tables 5 and 6, respectively. Exchange power with the main grid limitations (i.e. P_{mg}^{max}, P_{mg}^{min}) are 6 and -6 MW, respectively. Power fluctuation limitation at each time interval (i.e. GL) is considered 4 MW.

Table 5. Parameters of the Conventional Generation Units in case II

CG	a	b	P_{cg}^{min}	P_{cg}^{max}	R^{up}/R^{down}	$SU(g)$	$SD(g)$
	\$/h	\$/MWh	MW	MW	MW/h	\$	\$
1,2,3,4,5,6	40	60	0	2	0.6	50	50
7	30	50	0	2	0.6	45	45

Load, RG and prices deviations are considered 0.01, 0.3 and 0.3 of their average at each time step, respectively. Furthermore, selling prices are set to 0.8 of purchasing prices. Upper and Lower bounds of load, RG and prices are shown in Figs. 11, 12 and 13, respectively.

Table 6. Parameters of the Battery ESS in Case II

ESS	SoC_{min}	SoC_{max}	P_{es}^{min}	P_{es}^{max}	η^{dis}	η^{ch}
	MWh	MWh	MW	MW		
1	1	6	-1	1	0.95	0.95
2	2	8	-2	2	0.95	0.95

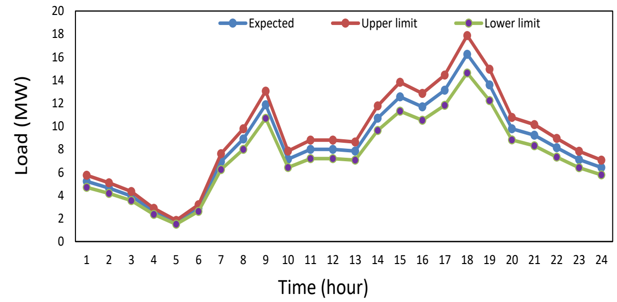

Fig. 11. Forecasted load demand and prediction interval in case II.

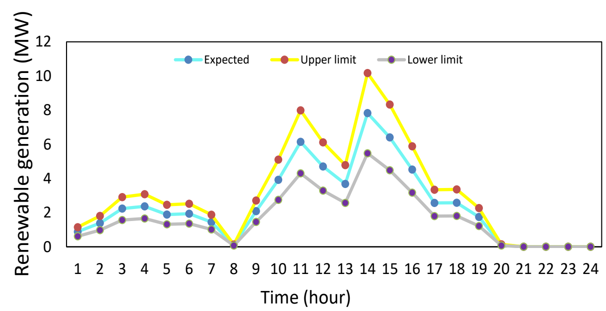

Fig. 12. Forecasted renewable power generation from the wind turbine and prediction interval in case II.

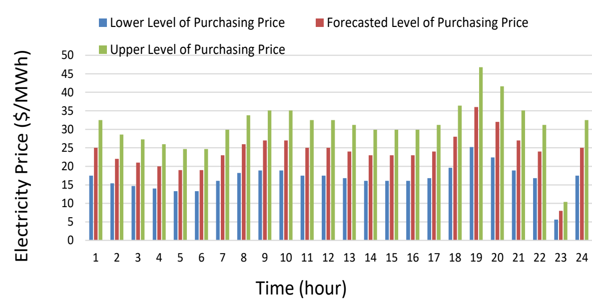

Fig. 13. Electricity price in case II.

In order to evaluate the performance of the proposed method considering load, RG and price uncertainties, the proposed method is applied to the microgrid in Fig. 14. Total operation costs for different degrees of robustness (i.e., different values of budgets) are calculated in Table 7. Worst-case scenario considering load and RG uncertainties is chosen via TOA method. It is depicted in Table 7 that increasing budget (i.e., degree of robustness) cause more costs to the microgrid operation which is consistent with robust energy management concept.

Results for budget value 12 are shown in the following. Obtained purchase and sell prices which are depicted in Figs. 15 and 16 show that the robustness has only increased the purchase prices and sell prices has remained equal to their forecasted amounts. Shifted load is shown

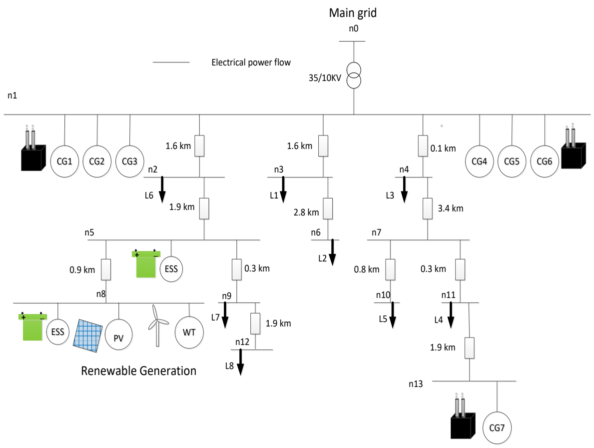

Fig. 14. Microgrid scheme in case II.

Table 7. Total Operation Cost for Different values of Budget

Budget (Γ)	Worst-Case Scenario	Total Operation Cost
6	Scen. 1 cycle 3	8631.3
12	Scen. 1 cycle 3	8895.1
18	Scen. 1 cycle 3	9273.6
24	Scen. 49 cycle 4	9708.2

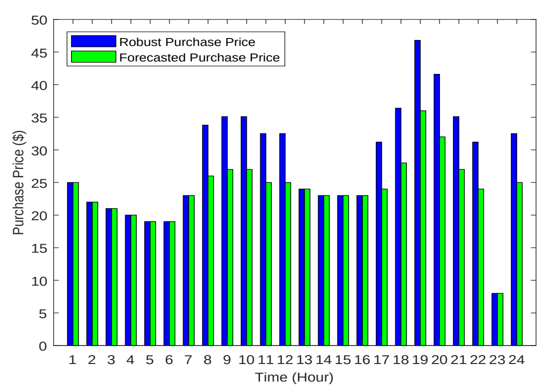

Fig. 15. Purchase prices resulted from robust energy management for $\Gamma = 12$ in case II.

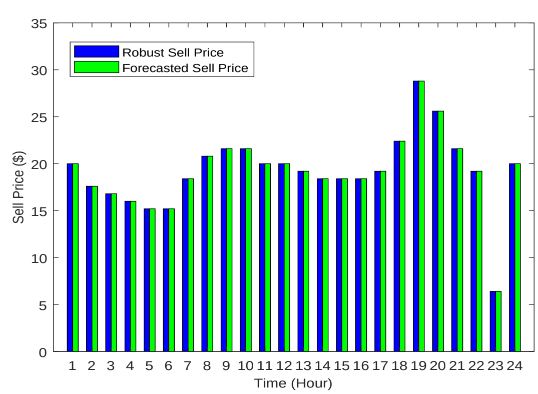

Fig. 16. Sell prices resulted from robust energy management for $\Gamma = 12$ in case II.

in Fig. 17 which helps to decrease the operation costs. Comparing Figs. 15 and 17 depict that load decreases during time slots that the robust purchase prices are high (i.e., during time slots 8-9 and 14-21). Output

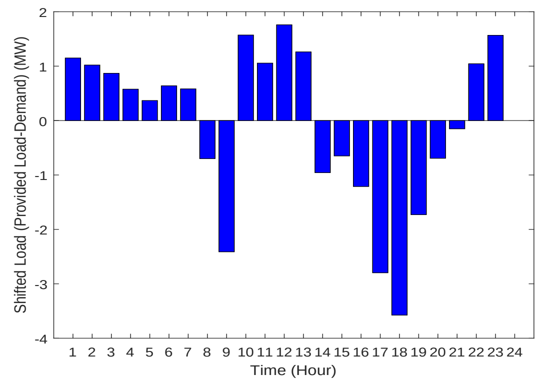

Fig. 17. Results of the demand response program for $\Gamma = 12$ in case II: the shedded and shifted loads.

power of CGs are depicted in Fig. 18. Output power of CG units 5 and 7 are only illustrated in Fig. 18 since other units' outputs are chosen 0. It is shown in Fig. 18 that the cheaper CG (i.e., CG7) produces higher level of power. Output power and energy level of battery ESSs are

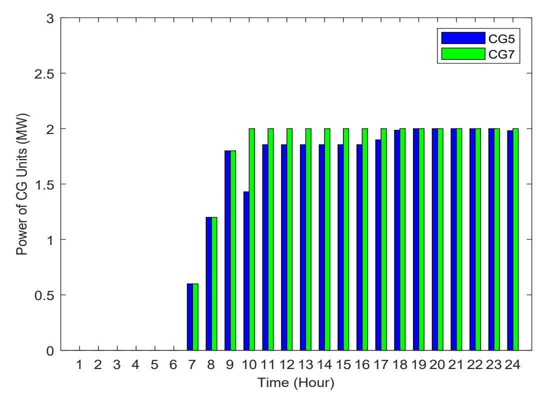

Fig. 18. Generation of CG5 and CG7 for $\Gamma = 12$ in case II.

depicted in Figs. 19 and 20, respectively. The exchanged power with the main grid is shown in Fig. 21.

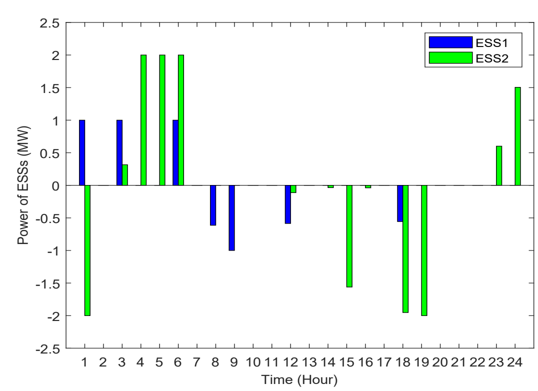

Fig. 19. Battery power for $\Gamma = 12$ in case II.

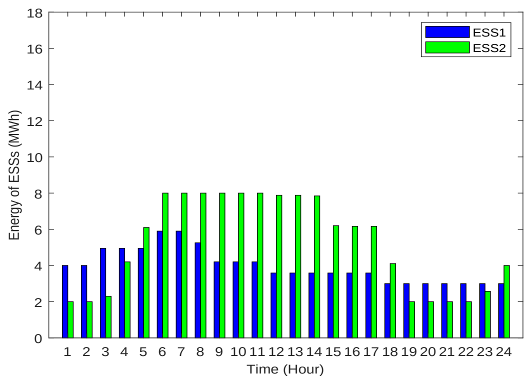

Fig. 20. Energy level in battery ESSs for $\Gamma = 12$ in case II.

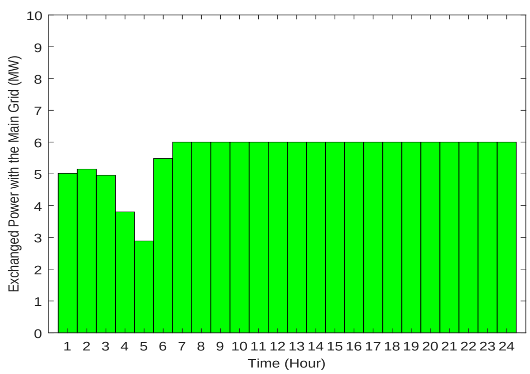

Fig. 21. The exchanged power with the main grid for $\Gamma = 12$ in case II.

5. Conclusion

Scenario-based robust energy management of the grid-connected microgrid is proposed in this study. The renewable generation, load demand and market price are considered as uncertain factors. The main contributions and conclusions are drawn as

- Robust decision is based on the worst-case scenario with the largest total cost. Taguchi's orthogonal array testing method is used to test the most possible worst-case scenarios.

- Two levels regarding the upper and lower limits for uncertain variables of renewable generation and load are considered. It is shown that the robust decision in this method does not necessitate scheduling with the largest load and the least renewable generation.

- In this study, Loads are considered controllable. Therefore, a demand response program is applied for the flexible loads in addition to robust programming. It is shown that, use of demand response programs can reduce the costs of robustness.

- Coordination of the storage with the renewable generation and conventional units' output power, helps to get the highest economic benefits, while remaining robust according to the designed energy management. Effectiveness of the proposed method is verified by the Monte Carlo simulations.
  As further research, it is of value to explore the EMS in a microgrid regarding optimal power flow constraints and minimizing line losses.

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