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Resilient Operation Scheduling of Microgrid Using Stochastic Programming Considering Demand Response and Electric Vehicles

A. Marami Dizaji[1], M. Saniei[1,*], K. Zare[2]

[1]Department of Electrical Engineering, Faculty of Engineering, Shahid Chamran University of Ahvaz, Iran.
[2]Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran

Abstract- *Resilient operation of microgrid is an important concept in modern power system. Its goal is to anticipate and limit the risks, and provide appropriate and continuous services under changing conditions. There are many factors that cause the operation mode of micogrid changes between island and grid-connected modes. On the other hand, nowadays, electric vehicles (EVs) are desirable energy storage systems (ESSs) because of clean transportation. Besides, energy storage systems are helpful to decrease power generation fluctuations arising from renewable energy sources (RESs) in new power systems. In addition, both sides (EV and RESs' owners) can gain a good profit by integrating EVs and RESs. Therefore, in this paper, a resilient operation model for microgrid is presented considering disasters and islands from the grid. In the proposed formulation, microgrid (MG) operator schedules its energy resources, EVs and ESSs in minimum cost considering demand response (DR) program and resiliency of the microgrid to islanding and uncertainties in market price, load, and generation of RESs. The impact of uncertainties is modeled in the scenario based framework as stochastic programming. The efficiency of presented method is validated on IEEE standard test system and discussed in two cases.*

Keyword: Demand response, microgrid, optimal resilient operation, stochastic programming, uncertainty.

NOMENCLATURE

Indices

b, Ω^{ESS}	Index and set of energy storage systems
$Cost^{MG}$	Total operation cost of microgrid ($)
$Cost_{net}^{Pur}$	Net cost of purchasing/selling power from/to main grid ($)
$Cost_{EV}^{\deg}$	Degradation cost of EVs battery ($)
C_i^{MT}	Operation cost of MTs ($/MW)
$CST_{i,t}^{MT}$ $CSD_{i,t}^{MT}$	Start-up/Shut-down cost of MT ($)
n, Ω^{bus}	Index and set of buses
$P_{i,t,s}^{MT}$, $Q_{i,t,s}^{MT}$	Active and Reactive power Production of MT (MW, MVAr)
s, S	Index and set of scenarios
t, T	Index and set of Time intervals
v, Ω^{EV}	Index and set of electric Vehicles
w, Ω^{W}	Index and set of wind turbines

Parameters

$C_{\deg}$	Degradation Cost of battery ($/MW)
$DR_{\max}^{n}$	Maximum value of shifted load (MW)
$E_{b,\min}^{ESS}$, $E_{b,\max}^{ESS}$	Min/Max stored energy (MWh)
$G_{n,m}$, $B_{n,m}$	Line conductance and susceptance between buses n , m (Ω^{-1})
$m_{b,t}^{ESS,ch}$, $m_{b,t}^{ESS,dis}$	Charge/ Discharge status of storage unit *b* at the time t
$P_{b,\min}^{ESS,dis}$, $P_{b,\max}^{ESS,dis}$	Min/Max discharge capacity of storage unit b (MW)
$\eta_v^{EV,ch}$, $\eta_v^{EV,dis}$	Charge/discharge cycle efficiency of vehicle v
$SOC_{\min}^{v}$, $SOC_{\max}^{v}$	Min/Max capacity of EV's battery
$P_{v,\min}^{EV,ch}$, $P_{v,\max}^{EV,ch}$	Min/Max charge power of EV (MW)
$P_{v,\min}^{EV,dis}$, $P_{v,\max}^{EV,dis}$	Min/Max discharge power of EV (MW)
$U_{v,t}^{EV,ch}$, $U_{v,t}^{EV,dis}$	Status of charge/discharge of EV
$\Delta D_{v,t}^{v}$	The covered distance (km)
$\eta_b^{ESS,ch}$ $\eta_b^{ESS,dis}$	Charge/discharge cycle efficiency of storage unit b

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*Corresponding author:
E-mail: m.saniei@scu.ac.ir (M. Saniei)
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$inc_{\max}^{n}$	Increased load of bus n (MW)
Δt	Operation time interval (h)
$P_{b,\min}^{ESS,ch}$ $P_{b,\max}^{ESS,ch}$	Min/Max charge capacity of storage unit b (MW)
$SL_{n,m}^{\max}$	Maximum apparent power flow buses n , m (MVA)
$V_{n}^{\min}$, $V_{n}^{\max}$	Min/Max voltage in bus n
$\rho_{t,s}$	Hourly electricity price (\$/MW)
$P_{i,\min}^{MT}$, $P_{i,\max}^{MT}$	Min/Max output power of MT (MW)
$u_{i,t}^{MT}$	Binary variable, 1 if the MT is committed; otherwise it is 0
MUT^{i} , MDT^{i}	Minimum up/down time limits of MT (MW/hr)
$P_{t,s}^{buy}$, $P_{t,s}^{sell}$	Buying/Selling active power from/to main grid (MW)
$Q_{t,s}^{buy}$	Buying reactive power from main grid (MVAr)
$P_{w,t,s}^{W}$	Wind output power (MW)
$PL_{t,s}^{n,m}$, $QL_{t,s}^{n,m}$	Active and Reactive power flows between buses n and m (MW/MVAr)
$P_{n,t,s}^{D}$, $Q_{n,t,s}^{D}$	Real/Reactive served load at bus n (MW/MVAr)
$V_{n,t,s}$	Voltage of bus n at hour t in scenario s
$\delta_{n,t,s}$, $\delta_{m,t,s}$	Voltage angle at bus m and n at hour t (rad)
$P_{t,s}^{DR,n}$	Load of bus *n* at time *t* in scenario *s* during DRP (MW)
$DR_{t,s}^{n}$	Percentage of load shifting
$P_{t,s}^{0,n}$	Initial flexible demand of bus *n* at time *t* in scenario *s* (MW)
$load_{t,s}^{n}$	Load of bus n at time *t* in scenario *s* (MW)
$ldr_{t,s}^{n}$	Shifted load from other hours to hour *t* (MW)
$inc_{t,s}^{n}$	Incremental load factor
$SOC_{t,s}^{v}$	State of charge in unit *v* at the time t in scenario s
$P_{v,t,s}^{EV,ch}$, $P_{v,t,s}^{EV,dis}$	Charge/Discharge power in vehicle *v* (MW)
Variables	
$E_{b,t,s}^{ESS}$	Stored energy in unit *b* at the end of each period (MWh)
$P_{b,t,s}^{ESS,ch}$, $P_{b,t,s}^{ESS,dis}$	Charge/Discharge power in unit *b* at the end of each period (MW)
OF	Objective function (\$)

1. INTRODUCTION

A microgrid includes distributed energy resources (DERs), different types of loads, and energy storage systems that are connected by a medium-voltage system within a geological area [1]. The MG can be operated in both islanded and gird-connected modes recovering the local flexibility and reliability of electric grids [2].

Recently, the environmental events such as severe hurricanes, blizzards, and thunderstorms encourage power system operators to have an efficient grid, highlighting the concept of resiliency (it means the capability of a power network to suffer intensive disturbances and reduce the harmful influences of such disasters). An effective way to enhance the power system resiliency is employing MGs in islanding mode (especially when natural catastrophes occur) [3], [4]. The aim of enhancing resilience can be achieved not only by infrastructure reinforcement but also by taking operational measures to realize quick recovery after the disaster [5]. A resilience-oriented proactive methodology, which aims at enhancing the preparedness of multiple energy carrier microgrids against an approaching hurricane is addressed in [6]. Applications of MG to the power system resilience are widely addressed in the literature.

The available methods for forecasting probable islanding scenarios are reviewed in [7]. The islanding scenarios are resulted from natural disasters; therefore, these random parameters are presented in the MG scheduling procedure accompanied by their related probabilities.

Recently, interests to operate renewable energy sources (RESs) are increasing because of the environmental concerns and growing scarcity of the fossil fuel. Therefore, evaluating an MG integrated with RESs (e.g., wind and solar) is necessary in power system studies [8]. Nevertheless, evaluation of simultaneous MG and RESs is not simple because of many uncertain variables in power generation and reliability of RESs [9]. A new method based on intelligent algorithm has addressed in [10] to optimal operate the demand side management in the presence of DG units and demand response.

In a centralized controlled MG, MG central controller (MGCC) determines energy bids that are resulting from estimation of power market prices, load and renewable energy output. Unit commitment of day ahead could be established according to market price, forecasted demand, and the status of units. The MGCC sets the bids, the set-point of generation units, the state of charge of energy storage units and amount of demand after applying demand response program (DRP).

Furthermore, the bidding and dispatch strategy of MGCC have to maximize the whole revenue of MG resulted from market participation while minimizing the operation cost of facilities in islanded and grid- connected modes [11]. As obvious, electric vehicle (EV) would be another significant element of power system in the future, because they can decrease concerns about the air pollution and fossil fuel scarcity [9]. The emission reducing objective is attained by optimum and proper exploitation of the vehicles as loads and energy storages in the MG with RESs [12–15]. Beside these benefits, the linking of EVs to the power grid may create numerous technical challenges that require to be investigated appropriately.

Vehicle-to-Grid (V2G) concept is related to electrical energy storage technology which has the competence to permit bidirectional power flow amid the electric power network and a vehicle's battery [16]. Regarding the V2G competence, the state of charge of a vehicle's storage can increase or decrease, depending upon the grid's demands and revenues.

Extensive usage of aggregated EVs is suggested in [17] to overcome the insignificant storage capacity of an EV. EV parking lots have been envisaged as new players and their role is gathering the EVs to attain significant storage capacity from slight battery capacity of EVs, in the contingency conditions. An energy management model for a charging park is addressed in [18], where, the grid-connected charging park contains a photovoltaic system as well as plug-in hybrid EVs. An electric vehicle (EV) aggregator, as an agent between power producers and EV owners, participates in the future and pool market to supply EVs' requirement. The problem of optimal decision making of an EV aggregator in a medium-term horizon under uncertain conditions has investigated in [19].

Since the optimal scheduling of MG with EVs is a fundamental qualification for revealing the advantages of MGs, a stochastic resiliency-oriented method is established in this paper.

The main contribution of this paper is highlighted as follow:

- Taking into account the four uncertainties of renewable energy production, the amount of grid consumption, the price of electricity purchased from the upstream grid and the connection or non-connection of the grid to the upstream grid.
- Reduction of operation costs and more resilient against islanding accidentally microgrid by incorporating intelligent network technologies such as energy storage systems and demand response programs.
- Impact evaluation of using energy storage systems and demand response programs in the uncertainty management of microgrid load, network pricing and renewable resource generation.
- Offering optimal planning for electric vehicles in order to optimize the operation of the microgrid.
- Considering an IEEE network for microgrid by taking into account voltage and line constraints in the form of power flow.

This paper is divided into five sections. Section 2 describes the principles, components' characteristics and demand response and resiliency concepts. In the third section, the mathematic framework of presented problem has been outlined and in the fourth section established case studies has been analyzed. Some conclusions are drawn in the final section.

2. MATHEMATICAL MODELING OF SYSTEM ELEMENTS AND RESILIENCY CONCEPT DESCRIPTION

In this section, the modeling of power system components such as energy resources, electric vehicles, storage systems, and demand response as well as resiliency concept description, are presented. Microgrid is a group of interconnected loads and distributed energy resources that acts as a single controllable entity with respect to the grid [20]. In simple terms, microgrid is a small energy cell that provides the energy to its consumers from upper grid in grid connected mode and its resources such as microturbines and RESs.

2.1. Wind turbine model

The wind turbines are one of the commonly used RESs for the energy systems that are categorized into variable speed or constant speed [21]. In this paper, for the operation horizon times wind speed is forecasted and the operation management has been schemed based on these values. It is assumed that the power generation of wind turbine is based on the curve illustrated in Fig. 1 [22].

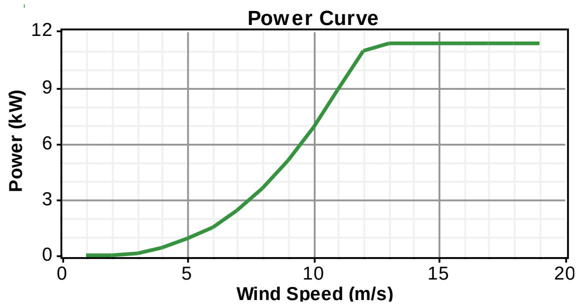


Fig. 1. Output power of a 10 kW-wind turbine in Bergary [22]

The fitted curve to this figure is determined as follows:

$$P^{WT}(v_{t,s}) = \frac{p_1 v_{t,s}^2 + p_2 v_{t,s} + p_3}{q_1 v_{t,s}^2 + q_2 v_{t,s} + q_3} \quad (1)$$

$$0 \le P_{t,s}^{WT} \le P^{WT}(v_{t,s}) \quad (2)$$

where, $v_{t,s}$, is wind speed at time t in the scenario s. Also, the values of constants p_1, p_2, p_3, q_1, q_2, and q_3 are 4.936, -20.22, 31.04, 1, -20.91, and 154.4, respectively.

2.2. ESS Model

Batteries and flywheels are important energy storage systems in power networks especially in islanded mode that provide uninterruptible power during disturbances and/or severe load changes. The ESSs have a limited energy storage capacity due to their physical limitations. Rechargeable battery is commonly device and is considered in this work. The operation characteristic of storage units and energy balance constraint can be defined as an operation problem using (3)-(6) [23]:

$$E_{b,t,s}^{ESS} = E_{b,t-1,s}^{ESS} + \Delta t \times \left[\eta_b^{ESS,ch} P_{b,t,s}^{ESS,ch} - \frac{P_{b,t,s}^{ESS,dis}}{\eta_b^{ESS,dis}} \right] \quad (3)$$

$$P_{b,\min}^{ESS,ch} \times m_{b,t}^{ESS,ch} \le P_{b,t,s}^{ESS,ch} \le P_{b,\max}^{ESS,ch} \times m_{b,t}^{ESS,ch} \quad (4)$$

$$P_{b,\min}^{ESS,dis} \times m_{b,t}^{ESS,dis} \le P_{b,t,s}^{ESS,dis} \le P_{b,\max}^{ESS,dis} \times m_{b,t}^{ESS,dis} \quad (5)$$

$$E_{b,\min}^{ESS} \le E_{b,t,s}^{ESS} \le E_{b,\max}^{ESS} \quad (6)$$

It should be noted that the battery does not charge and discharge simultaneously. Therefore, binary variables $m_{b,t}^{ESS,ch}$ and $m_{b,t}^{ESS,dis}$ are implemented to model the status of energy storage. Suppose $m_{b,t}^{ESS,ch}$ is the status of charge of unit b and $m_{b,t}^{ESS,dis}$ discharge status of storage unit b at the time t. The parameter Δt is operation time interval which is considered 1 hour in this paper.

As expressed in Eq. (3) the stored energy in unit b at the end of each period ($E_{b,t,s}^{ESS}$) is determined by the previous period storage level and difference of charging ($P_{b,t,s}^{ESS,ch}$) and discharging power ($P_{b,t,s}^{ESS,dis}$) during this period. The charging and discharging power of ESS are bounded by Eq. (4) and Eq. (5), respectively. The limitation for the ESS capacity is defined in Eq. (6).

2.3. EV model

EVs are expected to have a significant percentage of the vehicle market sales in the next years. The additional energy requirements for charging their batteries may affect the network operation, in terms of stability and reliability, especially when these are synchronized with the system peak demand. This notation will present power system operators with the challenges to efficiently integrate EVs into power systems by drawing out their ability to behave as manageable loads [24].

The operation modelling of EV is described in (7)–(12) [20].

$$SOC_{t,s}^{v} = SOC_{t-1,s}^{v} + \eta_v^{EV,ch} P_{v,t,s}^{EV,ch} - \frac{P_{v,t,s}^{EV,dis}}{\eta_v^{EV,dis}} - P_{v,t,s}^{EV} \quad (7)$$

$$SOC_{\min}^{v} \le SOC_{t,s}^{v} \le SOC_{\max}^{v} \quad (8)$$

$$P_{v,\min}^{EV,ch} \times U_{v,t}^{EV,ch} \le P_{v,t,s}^{EV,ch} \le P_{v,\max}^{EV,ch} \times U_{v,t}^{EV,ch} \quad (9)$$

$$P_{v,\min}^{EV,dis} \times U_{v,t}^{EV,dis} \le P_{v,t,s}^{EV,dis} \le P_{v,\max}^{EV,dis} \times U_{v,t}^{EV,dis} \quad (10)$$

$$P_{v,t}^{EV} = \Delta D_{v,t}^{EV} \ \beta_v \quad (11)$$

$$U_{v,t}^{EV,ch} + U_{v,t}^{EV,dis} \le 1 \quad (12)$$

Equation (7) declares the energy balance of EVs.
As shown the EVs' state of charge ($SOC_{t,s}^{v}$) is considered to be dependent on scenarios. The ($P_{v,t,s}^{EV,ch}$ and $P_{v,t,s}^{EV,dis}$) are charging and discharging power, respectively. It should be noted that status of charge and discharge of EV's ($U_{v,t}^{EV,ch}$ and $U_{v,t}^{EV,dis}$) are considered as here- and-now variables since charge and discharge status cannot be dependent on the scenarios. The maximum and minimum capacity of EV's battery is satisfied according to (8) and maximum and minimum charge and discharge power of EVs are limited by (9)–(10), respectively. In (11), the consumption power of EVs ($P_{v,t}^{EV}$) is determined using linear equation according to distance ($\Delta D_{v,t}^{EV}$). Equation (12) states the binary mode of charging and discharging for the EV's storage units.

2.4. Resiliency concept

The resiliency concept in the microgrid is a different issue from the reliability. In the other terms, resiliency of the microgrid must lead to some structures that provide some characteristics for the microgrid, which can operate autonomously and in a manner that helps mitigate power grid disturbances and strengthen grid resilience. The main features of the resilient microgrid are [25]:

- Continue to operate when the main power grid is faced with failures
- Serve as a grid resource for faster system response and recovery
- Integrating the renewable energy and distributed energy resources
- Moving toward a clean energy future

In this paper, the status of microgrid connection to the main grid (distribution network) is considered to be an uncertain parameter for the operation period. In order to obtain the proper operation schedule of energy resources according to islanded and grid-connected modes, the problem is formulated as a two-stage stochastic problem. Variables of the problem are classified into two categories based on two stage stochastic programming. The first category includes certain variables (known as first-stage or *here-and-now*) that do not depend on the scenarios, while second category includes uncertain variables (known as second-stage or *wait-and-see*) that depend on scenarios. The variables of purchasing and selling power from/to main grid in grid-connection status are considered as uncertain parameters.

2.5. DR Model

In DR program, each consumer can manage and change its demand. Different kinds of consumers respond differently to the same market price. The behavior of consumers can be modeled through the utility or benefit function, aiming maximization of their welfare. In this way, electrical loads can be classified as shift-able and non-shift-able loads [26]. The first one includes the loads that can be operated every time during a day or a specified time interval. The second one includes loads that cannot be shifted in a day. Information about how the electricity demand is affected by the time of use program has been discussed in [27].

In this manner, microgrid operator can manage the consumption of its shift-able loads. Based on load characteristics including demand profile and price elasticity, the authors of [28] have driven a comprehensive economic model for responsive demand. The main aim of the demand response is to adapt the users' power consumption to the time varying market prices. In other terms, the users shift their time of use from high market price hours to the low market price periods. Along with DR, the MG adjusts its consumption regarding the market prices in order to minimize the cost of energy supply. In this literature, it is assumed that the specified portion of the MG's load can be participated in the DR program. Equation (13) describes MGs load during DRP [24].

$$P_{t,s}^{DR,n} = \left(1 - DR_{t,s}^{n}\right) \times P_{t,s}^{0,n} + ldr_{t,s}^{n} \tag{13}$$

Where, $P_{t,s}^{0,n}$ indicates the initial flexible demand of bus n at time t in scenario s. The percentage of load shifting from hour t is defined by $DR_{t,s}^{n}$ and $ldr_{t,s}^{n}$ indicates the shifted load from other hours to hour t. Following complementary equations limit the portion of load that could be shifted to other intervals.

$$DR_{t,s}^{n} \le DR_{\max}^{n} \tag{14}$$

$$load_{t,s}^{n} \le inc_{t,s}^{n} \times P_{t,s}^{0,n} \tag{15}$$

$$load_{t,s}^{n} = ldr_{t,s}^{n} - \left(DR_{t,s}^{n} \times P_{t,s}^{0,n}\right) \tag{16}$$

The incremental load factor $inc_{t,w}^{n}$ is limited as follows:

$$inc_{t,s}^{n} \le inc_{\max}^{n} \tag{17}$$

where, $DR_{\max}^{n}$ and $inc_{\max}^{n}$ represent the maximum value of shifted load and increased load of bus n. It is supposed that the total consumed energy of flexible loads will be same before and after implementing DR. This fact is considered as follows.

$$\sum_{t=1:T} ldr_{t,s}^{n} = \sum_{t=1:T} DR_{t,s}^{n} \times P_{t,s}^{0,n} \tag{18}$$

3. PROBLEM FORMULATION

In this paper, the energy management problem of a microgrid including uncertainties of RESs, islanding, electric demand and prices is modeled as a stochastic mixed integer non-linear programing (MINLP) over a specific horizon (T) with discrete time steps t ($t \in T$) and scenario set s ($s \in S$). In this study, a day is divided into 24 time intervals and scenarios are considered as forecasted events for the time period. Uncertain parameters includes output power of wind turbines, consumption of loads, electrical prices and status of main circuit breaker (when it is open, microgrid operates in island mode and vice versa). The state of grid connection is predicted based on heuristic failure prediction technique that will be described in the next section. Also, the flowchart of proposed operation management has been illustrated in Fig 2, which its details are discussed in following.

3.1. Uncertainties

In this study, uncertainties are classified as real and binary parameters. Real uncertain variables are power generation of wind turbine (it depends on wind speed), price of electricity transactions between microgrid and the main grid, and demand. Binary variables include islanding statuses which show the contingency of grid failures. The methods of uncertainty studies have been presented in the [29] and [30]. In this paper, regarding to the similarity of distribution functions of wind turbine power and weibul, the parameter of weibul distribution function for the implemented wind turbine is adobted based on [31]. The weibul distribution function [32] is used to generate scenarios for the output power of wind turbines. The normal distribution function is implemented for the consumption loads and the electricity prices [33].

The heuristic failure method [34] is used to predict the islanding status for future hours based on regional climate condition, because disasters are main reasons of microgrid islanding. This method can create good prediction for the operating hours, because the time intervals are short [34].

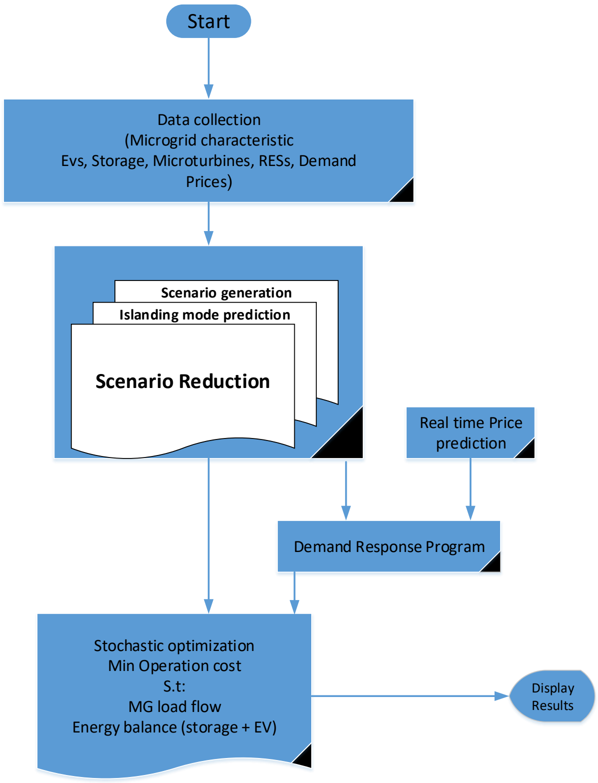


Fig 2. The proposed operation scheme

3.2. Objective functions and constraints

The problem of resilience-oriented microgrid is modeled as a two-stage stochastic problem. The goal of microgrid management is to achieve minimum expected cost [35-36]. Therefore, the total cost of the microgrid management can be written as follows.

$$OF = Min \ \{Cost^{MG} + Cost_{net}^{Pur} + Cost_{EV}^{\deg}\} \tag{19}$$

where,

$$Cost^{MG} = \sum_{s\in S} \pi_s \times \sum_{t\in T} \left(\sum_{i\in\Omega^{MT}} C_i^{MT} \times P_{i,t,s}^{MT} + CST_{i,t}^{MT} + CSD_{i,t}^{MT} \right) \tag{20}$$

$$Cost_{net}^{pur} = \sum_{s\in S} \pi_s \times \sum_{t\in T} \rho_{t,s} \left(P_{t,s}^{buy} - P_{t,s}^{sell} \right) \tag{21}$$

$$Cost_{EV}^{\deg} = \sum_{s\in S} \pi_s \times \sum_{t\in T} \sum_{v\in\Omega^{EV}} C_{\deg} \times DE_v^{t,s} \tag{22}$$

The first term of objective function (19) ($Cost^{MG}$) denotes the total operation cost of microgrid within the operation period, including operation, start-up and shot-down costs of microturbines (Eq. (20)). The second term ($Cost_{net}^{pur}$) includes net cost of purchasing/selling power from/to main grid (Eq. (21)). Finally, the third term ($Cost_{EV}^{\deg}$) consists of the degradation cost of EV's battery due to energy discharge (Eq. (22)) [37]. The terms of equations (20) to (22) will be described in next sections. Equation (23) explains the generation ($P_{i,t,s}^{MT}$) of each microturbine (MT) is limited by its maximum ($P_{i,\min}^{MT}$) and minimum outputs ($P_{i,\max}^{MT}$).

$$P_{i,\min}^{MT} \times u_{i,t}^{MT} \le P_{i,t,s}^{MT} \le P_{i,\max}^{MT} \times u_{i,t}^{MT} \qquad \forall i \in N_{MT},\ t\in T, s\in S \tag{23}$$

In (23), $u_{i,t}^{MT}$ is a binary variable that shows the commitment status (it will be 1 when the microturbine is committed and it will be 0 when the microturbine is not operated). In addition, minimum on-time and off-time limits of MT are written as (24) and (25), respectively.

$$u_{i,t}^{MT} - u_{i,t-1}^{MT} \le u_{i,TU(i,t,h)}^{MT} \qquad \forall i \in \Omega^{MT}, \{t,h\}\in T \tag{24}$$

$$u_{i,t-1}^{MT} - u_{i,t}^{MT} \le u_{i,TD(i,t,h)}^{MT} \qquad \forall i \in \Omega^{MT}, \ \{t,h\}\in T \tag{25}$$

where, $TU(i,t,h)$ and $TD(i,t,h)$ are expressed as follows.

$$TU(i,t,h) = \begin{cases} t+h & h < MUT^i \\ 0 & h \ge MUT^i \end{cases} \qquad \forall i \in \Omega^{MT}, \ \{t,h\}\in T \tag{26}$$

$$TD(i,t,h) = \begin{cases} t+h & h < MDT^i \\ 0 & h \ge MDT^i \end{cases} \qquad \forall i \in \Omega^{MT}, \{t,h\}\in T \tag{27}$$

Active and reactive power balances for a microgrid are stated by (28) and (29).

$$\begin{aligned} &\sum_{n\in N_{bus}} \mu_{n,t,s}^{MG}\left(P_{t,s}^{buy} - P_{t,s}^{sell}\right) + \sum_{i\in\Omega_n^{MT}} P_{i,t,s}^{MT} + \\ &\sum_{w\in\Omega_n^{W}} P_{w,t,s}^{W} + \sum_{b\in\Omega_n^{ESS}} \left(P_{b,t,s}^{ESS,dis} - P_{b,t,s}^{ESS,ch}\right) + \\ &\sum_{v\in\Omega_n^{EV}} \left(P_{v,t,s}^{EV,dis} - P_{v,t,s}^{EV,ch} - P_{v,t,s}^{EV}\right) = \\ &\sum_{m\in\Omega_n^{bus}} PL_{t,s}^{n,m} + P_{n,t,s}^{D}. \quad \forall n\in N_{bus},\ t\in T,\ s\in S. \end{aligned} \tag{28}$$

$$\begin{aligned} &\sum_{n\in\Omega^{bus}} \mu_{t,s}^{MG}\left(Q_{t,s}^{buy}\right) + \sum_{i\in\Omega^{MT}} Q_{i,t,s}^{MT} = \\ &\sum_{m\in\Omega^{bus}} QL_{t,s}^{n,m} + Q_{n,t,s}^{D}. \quad \forall n\in\Omega^{bus},\ t\in T,\ s\in S. \end{aligned} \tag{29}$$

The $\mu_{n,t,s}^{MG}$, is a parameter that for the main grid connection bus similar to slack bus presents the mode of connection. It is supposed that n=1 is slack bus. Therefore for other buses $\mu_{n,t,s}^{MG}$ is equal to 0. It should be noted that for n= 1, uncertain parameter ($\mu_{'n=1',t,s}^{MG}$) is forecasted based on scenario generation technique which is described in the previous section.

It should be noted that, Ω^{MT}, Ω^{W}, Ω^{ESS} and Ω^{EV} are sets of microturbines, wind turbine, energy storage systems and electric vehicles which are located in bus n, respectively. The set Ω^{bus}, denotes buses which are connected to bus n via branches within the microgrid.

Equations (30) and (31) indicate active ($PL_{t,s}^{n,m}$) and reactive ($QL_{t,s}^{n,m}$) power flows between buses *n* and *m* at time *t* in scenario *s*, respectively. Also, (32) shows the AC power flow limitation between buses *n* and *m*.

$$\begin{aligned} PL_{t,s}^{n,m} &= G_{n,m}\left|V_{n,t,s}\right|^2 - \left|V_{n,t,s}\right|\left|V_{m,t,s}\right| \\ &\left\{G_{n,m}\cos\left(\delta_{n,t,s}-\delta_{m,t,s}\right)+B_{n,m}\sin\left(\delta_{n,t,s}-\delta_{m,t,s}\right)\right\} \end{aligned} \tag{30}$$

$$\begin{aligned} QL_{t,s}^{n,m} &= -B_{n,m}\left|V_{n,t,s}\right|^2 - \left|V_{m,t,s}\right|\left|V_{m,t,s}\right| \\ &\left\{G_{n,m}\sin\left(\delta_{n,t,s}-\delta_{m,t,s}\right)-B_{i,j}\cos\left(\delta_{n,t,s}-\delta_{m,t,s}\right)\right\} \end{aligned} \tag{31}$$

$$-SL_{n,m}^{\max} \le \sqrt{\left(PL_{t,s}^{n,m}\right)^2+\left(QL_{t,s}^{n,m}\right)^2} \le SL_{n,m}^{\max} \tag{32}$$

The constraints corresponding to voltage amplitude and angle are applied by (33) and (34).

$$V_n^{\min} \le V_{n,t,s} \le V_n^{\max} \tag{33}$$

$$\begin{cases} V_{n,t,s}=1 \\ \delta_{n,t,s}=0 \end{cases} \quad n = slack \tag{34}$$

Energy exchange constraints of microgrid with main grid due to security and equipment limitations are represented as (35)-(36).

$$P_{t,s}^{buy} \le P_{\max}^{MG} \times u_{t,s}^{MG} \tag{35}$$

$$P_{t,s}^{sell} \le P_{\max}^{MG} \times u_{t,s}^{MG} \tag{36}$$

4. CASE STUDY AND DISCUSSION

In order to verify the model, proposed technique is tested on a 33-bus microgrid (Fig. 3) under two cases. In case 1, the problem is solved ignoring islanding uncertainty, while this uncertainty is considered in case 2. The scheduling period is a 24-hour interval in presence of uncertainties.

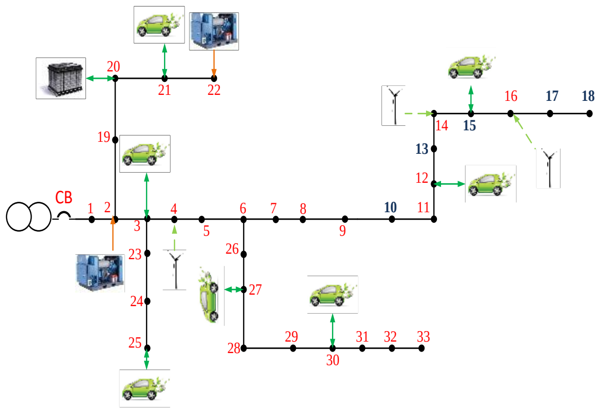


Fig.3. 33-bus microgrid

This microgrid includes two microturbines on buses 2 and 22, three wind turbines on buses 4, 14 and 16, one 200 kW-battery (energy storage system) on bus 20, and seven electric vehicles with the same capacity on buses 3, 12, 15, 21, 25, 27 and 30. It is assumed that power generation curve of wind turbines are according to Fig. 1. The maximum allowable capacity, minimum charge/discharge rate, initial charge, and efficiency of battery are 200 kWh, 100 kWh, 5 kW, and 100%, respectively [38]. Also, the flexible loads that can participate in DR program are considered on buses 10, 13, 15, 17 and 18. The efficiency of charging/discharging of PEV is considered to be 100%.

The resistance and reactance of branches are presented in Table 1. The base values for the voltage and apparent power are 12.66 kV and 8 MVA, respectively. In addition, the expected value of day-ahead prices is illustrated in Fig 4.

The proposed problem is formulated as a mixed integer non-linear programming (MINLP) problem in GAMS and solved by DICOPT solver [39]. Microgrid uncertainties such as failure in grid connection, load forecast error, and errors in prediction of distributed generation are formulated by scenario generation technique. Then, the backward scenario reduction method [40] is used to decrease the time of calculations. This method determines a closest subset of initial generated scenario and is faster than other scenario reduction techniques [40].

The voltage magnitudes of microgrid's buses in both cases are shown in Fig. 5. According to Fig. 5-(a), in case 1, the voltage magnitude increases on buses that reactive power is injected to them. It can be observed that the voltage profile changes slightly because of interchange of active and reactive powers between MG and the main grid. The voltage of bus connected to the main grid (slack bus) is fixed on 1.05 p.u. As shown in Fig. 5-(b), the voltage profile changes strongly in comparison with case 1, while MG uses its own reactive resources and distributed generation units. The reason is islanding microgrid from the main grid. It should be noted that in the grid connected mode, voltage magnitude of grid connected bus is considered to be 1.05 p.u.

Table 1. The characteristics of 33-bus modified microgrid

Branch	Start	End	Resistance (p.u)	Reactance (p.u)
1	1	2	0.0046	0.0023
2	2	3	0.0246	0.0125
3	2	19	0.0082	0.0078
4	3	4	0.0183	0.0093
5	3	23	0.0225	0.0154
6	4	5	0.019	0.0097
7	5	6	0.0409	0.0353
8	6	7	0.0093	0.0308
9	6	26	0.0101	0.0051
10	7	8	0.0355	0.0117
11	8	9	0.0514	0.0369
12	9	10	0.0521	0.0369
13	10	11	0.0098	0.0032
14	11	12	0.0187	0.0062
15	12	13	0.0733	0.0576
16	13	14	0.027	0.0356
17	14	15	0.0295	0.0262
18	15	16	0.0372	0.0272
19	16	17	0.0643	0.0859
20	17	18	0.0365	0.0286
21	19	20	0.075	0.0677
22	20	21	0.0204	0.0239
23	21	22	0.0354	0.0468
24	23	24	0.0448	0.0354
25	24	25	0.0447	0.035
26	26	27	0.0142	0.0072
27	27	28	0.0529	0.0466
28	28	29	0.0401	0.0349
29	29	30	0.0253	0.0129
30	30	31	0.0486	0.048
31	31	32	0.0155	0.018
32	32	33	0.0251	0.0265

Moreover, the output power of wind turbines, ESS, microturbines, and EVs' state of charge during the operation time are shown in Figs. 6 to 9. Fig. 6 shows wind turbines provide the part of power demand with respect to their available powers, because power generation of wind turbines is limited by their capacity and wind speed.As shown in Fig. 7, battery is in charge for a longer time in case 2 in comparison with case 1 during operation time. The reason is that in case 1, charge and discharge process of battery need to follow only the market price, while in case 2, energy storage system has to tracks the islanding mode in addition to market price.

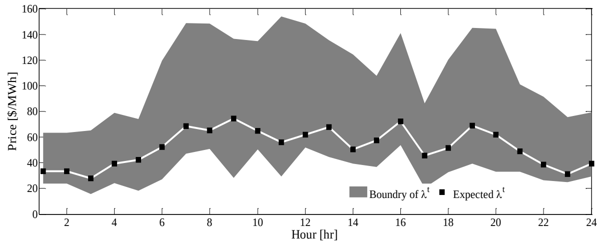
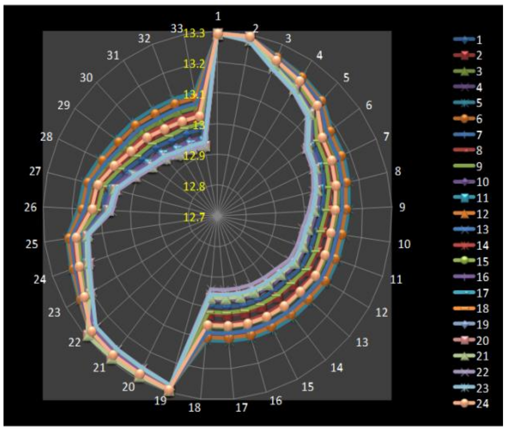
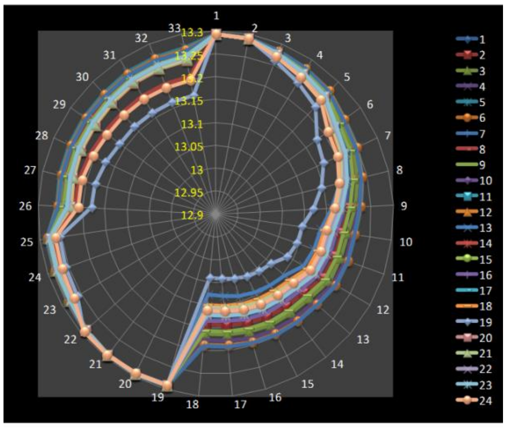


Fig. 4. The interval and expected day-ahead price



(a)– Case 1



(b)– Case 2

Fig.5. Voltage profile for the buses

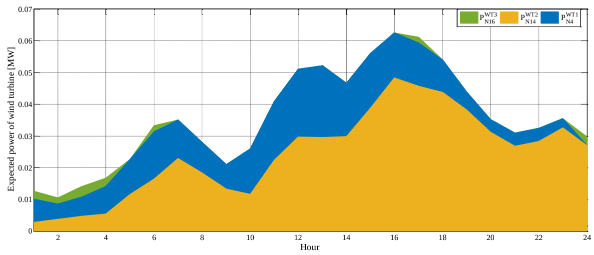


Fig. 6. The output power of wind turbines

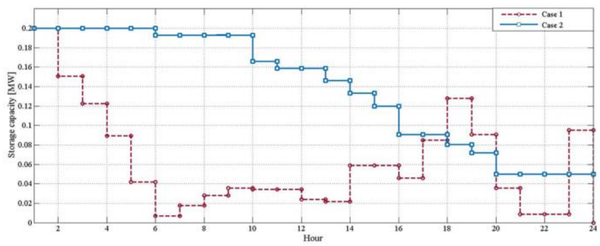


Fig.7. Storage state of charge

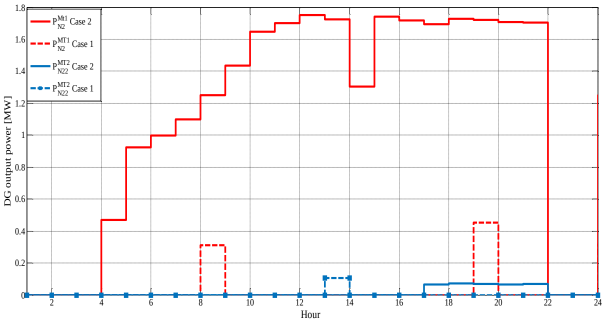
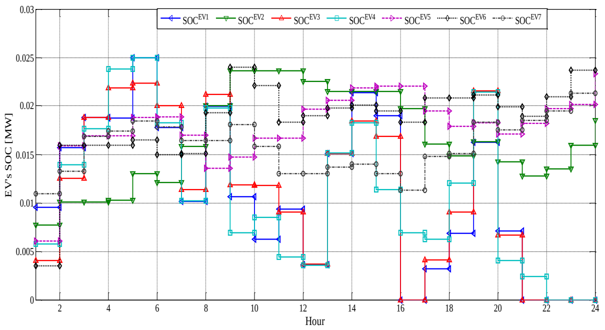
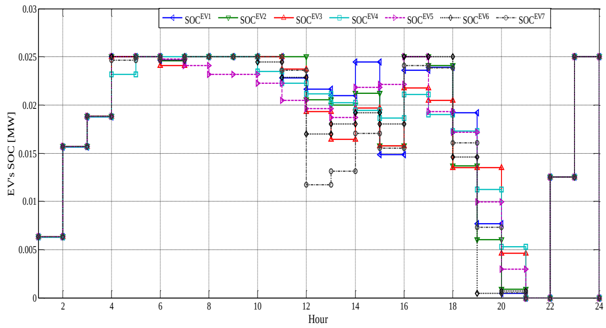


Fig. 8. The output power of microturbines for both cases

Due to Fig 8, the output power of microturbines in case 2 increases. For example, the output power of MT 1 on bus 2 increases with respect to its power in case 1. Also, the output power of MT 2 located on bus 22 is shifted to another interval.



(a)- Case 1

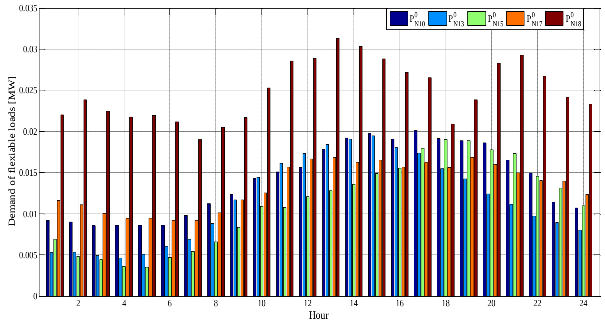


(b)- Case 2

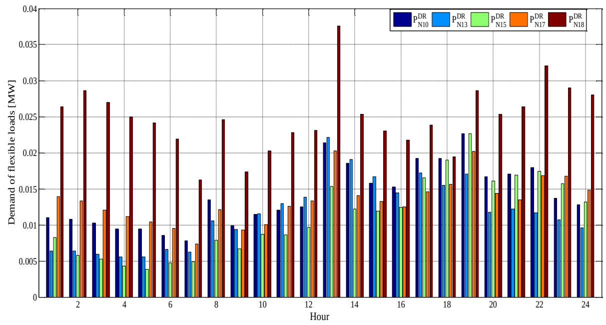
Fig. 9. EV's state of charge for grid connection mode (case 1) and uncertain island mode (case 2)

Fig. 9 shows that the vehicles charge at low power prices and discharge in hours with high power prices in order to feed the loads or sell the energy to the market. Comparing Fig. 9-(b) with Fig. 9-(a), it is clear that the EVs in the islanding mode (case 2) behave differently from the grid connected mode (case 1), i.e. the EVs save their energy for a longer time and release it in the other times in case 2.

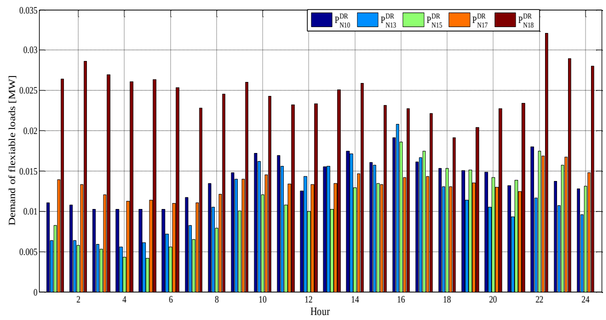
In order to decrease operation cost, microgrid owner prefer to shift the flexible loads from hours with high market price to hours with low prices. These changes in consumption pattern (see Figs. 10-(b) and (c)) can reduce the microgrid cost for both cases. The base loads that can participate in demand response program are illustrated in Fig. 10-(a).



(a)– Base load



(b)- Case 1



(c) Case 2

Fig.10. Demands of flexible loads for (a) base load, (b) after DR program in case 1, and (c) after DR program in case 2

Tables 2 and 3 list the values of objective function (operation cost) for both cases without and with considering demand response, respectively. According to these tables, the operation cost was reduced by 47% and 0.07% in cases 1 and 2, respectively, after applying DR program. This reduction illustrates the importance and effectiveness of proposed DR program in the scheduling problem.

Table 2. Operation costs regardless of DR program

Case 1	924.58 $
Case 2	967.33 $

Table 3. Operation costs considering DR program

Case 1	627.37 $
Case 2	966.62 $

5. CONCLUSION

In this paper, the optimal operation problem of a resiliency-oriented microgrid considering electric vehicles and demand responses was solved using a two-stage stochastic programming. The objective is to minimize the operation cost of microgrid in presence of DR resources, storage units, and electric vehicles taking into account the load flow constraints. In order to consider resiliency in scheduling of microgrid, a heuristic failure prediction model was used to formulate the uncertain islanding modes during operation time.

The simulation results reveal that considering the resiliency concept in energy management of a microgrid leads to increase operation costs. Nevertheless, a microgrid that includes microturbines, energy storage systems, electric vehicles, and wind turbines can feed its loads in islanding mode.

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