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Probabilistic reliability management of energy storage systems in connected/islanding microgrids with renewable energy

Ehsan Rahmani [a], Sirus Mohammadi [b,*], Mahmoud Zadehbagheri [a], Mohammadjavad Kiani [a,*]

[a] Department of Electrical Engineering, Yasuj Branch, Islamic Azad University, Yasuj, Iran
[b] Department of Electrical Engineering, Gachsaran Branch, Islamic Azad University, Gachsaran, Iran

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ABSTRACT

Energy storage systems (ESSs) are useful devices to ensure the reliable operation of microgrids especially those with high penetration of renewable energies. The microgrid operation is highly associated with scheduling of ESS units. Therefore, in this paper, a new algorithm for ESS scheduling has been suggested in order to manage MG in a reliable manner. Because reliability considering and cost minimization are conflicting objectives in ESS scheduling, the multi-objective optimization problem should be solved for optimal scheduling of ESS. Different operating strategy have been considered and their impact on ESS scheduling in the microgrid has been investigated. In order to properly consider the uncertainties associated with the multi-objective scheduling problem, probabilistic models have been presented for the parameters in the network and they are expressed as mixed integer linear programming (MILP) problems. Non-dominated sorting teaching learning-based optimization (NSTLBO) algorithm is employed to solve the MO problem. Scheduling plan is performed on both weekly and daily horizons in connected/islanding microgrid modes. By implementing this method on a modified 33-bus IEEE test system, the results endorse the effectiveness of the proposed scheme for enhancing the reliability of MGs.

1. Introduction

Nowadays, new communication technologies enable power systems to be improved to smart grids. One of the main components of smart grids is microgrids [1]. Microgrids supply their loads using their power generation sources or by the power received from the main grid, therefore they can provide sustainable and reliable power for the customers [2]. There are different resources in a microgrid to produce power including renewable energies and conventional generation units. High penetration of renewable energy sources can make some problems. Due to the intermittency of their input power, there is always the possibility that their forecasted power could not be realized. It means that there is insufficient power to meet load demand and increases the risk of customer interruptions in microgrids, especially in the islanding mode. These uncertainties can cause some difficulties in energy management and energy planning. Energy storage systems (ESSs) are employed in microgrids to overcome this problem. ESSs can save energy and give it back to microgrids when it was necessary.

ESS has multiple applications in microgrids such as load shifting [3], energy arbitrage [4], power quality improvement [5], reliability enhancement [6–7], cost minimization [8–9], loss reduction [10–11], and peak shaving [12]. Their main role in microgrids is energy arbitrage and cost minimization. To select the best usage of ESS in a microgrid, first, these units must be planned efficiently and optimally. A suitable implementation of ESS along with distributed energy resources (DERs) could increase the power generation of these intermittent resources. It enjoys the advantages of reducing costs and emissions of fossil fuel generation and maximizes the economic attractiveness of renewable technologies such as wind power and photovoltaics. Scheduling of the available resources is essential to achieve optimal performance of the grid and successfully satisfy the load requirements, reduce cost and emissions, and improve the reliability of MGs.

Various studies have been performed in the case of scheduling and planning of ESSs to enhance microgrid operation and management. Reliability evaluation of distribution systems with ESSs was firstly addressed to develop a method for modeling ESS units in reliability problems [13–14]. Some other research has investigated the optimal planning and scheduling of ESS units over the past decade. In [15], the authors proposed a model to determine the size of ESS with reliability constraints. Authors in [16] developed a tool for assessing different factors such as penetration level, operation strategies, and ESS capacities on operational reliability of MGs. They assessed the operational reliability of microgrids with wind turbines. Authors in [17–18], proposed a

* Corresponding authors.
E-mail addresses: S.mohammadi@srbiau.ac.ir (S. Mohammadi), ma.zadehbagheri@iau.ac.ir (M. Zadehbagheri), Mj.kiani@iau.ac.ir (M. Kiani).

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Nomenclature

$P_{ch,t}$	Power injected to ESS
$P_{disc,t}$	Power drawn from ESS
$P_{WF,t}$	Power output of wind farm
V_{ci}	Cut in speed
V_r	Rated speed
V_{out}	Cut out Speed
G_t	solar irradiance prediction
G_{std}	standard solar irradiance
η_{ch}	Charge efficiency of energy storage system
η_{dch}	Discharge efficiency of energy storage system
H	Timeslot index in island mode
δ_{ch}	charge binary indicators of ESSs
δ_{dch}	discharge binary indicators of ESSs
X	Vector of optimization variables
T	total number of hours
N_r	total number of renewable energy units
N_g	total number of distributed generating units
Ns	total number of storage units
N_{iter}	Number of interruption
F(.)	Cost-function of distributed generation
S^{Avg}	average SOC
L_i	load consumed in load point i
SOC_0	The initial level of SOC (%)
SOC^{max}	The maximum level of SOC (%)
SOC^{min}	The minimum level of SOC (%)
SOC	State of charge
WTG	Wind turbine generator
DER	Distributed energy resources
DG	Distributed generator
MT	Microturbine
ESS	Energy storage system
PV	Photovoltaic
RES	Renewable energy Source
P_{Smax}	Maximum import power (kW)
P_{Smin}	Allowable export power (kW)
E_n	Rated ESS Capacity (kWh)
WS	Wind speed
DU	Diesel Unit
MTTR	Mean Time To Repair
MTTF	Mean Time To Failure
LOLP	loss of load probability
LOLE	Loss of load expectation
EENS	expected energy not supplied
MCS	Monte Carlo Simulation
DoD	Depth of discharge
PDF	Probability distribution Function
MG	Microgrid
AC	Aging Cost
OC	Operation Cost
TLBO	Teaching learning-based optimization

stochastic framework to optimize ESS scheduling in microgrids. In this framework they optimize ESS scheduling in order to reducing MG cost and enhancing reliability. Ref. [19] proposed a protective model control for different strategies in microgrids and assessed the reliability of microgrids regarding the operation strategy and ESS units. In [20], an analytical approach is applied to determining the size, in terms of both power and energy capacity, of an ESS in such a way that meet a specified reliability target.

ESS scheduling has attracted much attention for energy management in microgrids in recent years. Optimal scheduling strategy broadly developed in literature [21–26]. Authors in [21] discussed that ESS scheduling in daily and weekly mode can enhance the operation performance of microgrid. Reference [22], authors proposed a framework which calculate the optimal size of ESS, while determining the optimal operation schedule of controllable components in a microgrid. In [23] scheduling of energy storage systems is considered in presence of renewable energy resources. Authors in [24] suggested a method that optimally schedule ESS to minimize operation cost of microgrid. In this method load requirements of cold, heat and electricity is satisfied in microgrids. In [25], a fundamental model is proposed by authors for scheduling of ESS in day-ahead power market. Authors in [26] developed a model of ESS considering economic and environmental perspectives. In that model, two objective functions were established to determine the optimal operation of ESS from the economic and environmental aspects. In [27] participation of the ESS unit in demand management and its application to the reliability evaluation. Authors in [28] developed a new reliability contribution function of BESS in wind farms. Ref. [29–30] explain some statistical methods

Increasing cycles and depth of discharge of a battery can cause degradation and reduce its lifetime [31]. Consequently, batteries with capacities of less than a specific value must be replaced, and this will impose huge investment costs on the microgrid. As a result, it's really important to take into account aging costs in the scheduling of ESSs. Batteries' lifetime and cycling have not been formulated explicitly in optimal scheduling for ESSs. In [32] an optimal BESS scheduling for MGs is proposed to solve the unit commitment problem stochastically, considering the aging cost of ESS units and the uncertainties in renewables and load. On the other hand, most studies carried out a day-ahead scheduling program for scheduling ESS in microgrids [33]. This scheduling horizon forces ESS units to have the same state of charge (SOC) at the start and end of the day even when it has high levels of SOC. This process can accelerate the aging of batteries and impose costs on the microgrid. Ignoring the aging cost of ESS as well as restricting the scheduling horizon to just in daily mode make big challenges. To overcome these challenges and problems we proposed a stochastic optimal scheduling method that includes degradation of ESS and depth of discharge is considered in both daily and weekly mode to optimally manage the microgrid. We concentrate on the optimal scheduling of ESSs in microgrids by using Teaching-Learning Based Optimization (TLBO) algorithm [34]. TLBO is a suitable method for finding optimal solutions to such problems since it does not require any algorithm-specific parameters. The contributions of this paper can be expressed as follows:

- Proposing a comprehensive model for optimal ESS scheduling, including a scheduling framework in a day-ahead and weekly time horizon.
- Modeling the aging cost of ESS units concerning both cycling and calendar factors. Dod and number of cycles of ESS are limited to a certain value to maximize battery energy throughput and reduce MG operation costs.
- Taking into account intrinsic uncertainty characteristics of all microgrid variables, including all uncertainties related to loads, electric price, renewable energy (PVs and WTs) outputs, and the duration of unscheduled islanding events.
- Studying microgrids in different operating modes (islanding and grid-connected mode) to maintain an appropriate trade-off between cost and reliability objective functions by the scheduling of ESS units considering the degradation cost of ESS.

The remainder of this paper is organized as follows: In section 2, the formulation of scheduling and planning problems are discussed. The proposed model of ESS and Microgrid reliability are explained in this section. In section 3 the scheduling optimization problem is broadly described and the suggested algorithm is presented. In section 4 the algorithm is implemented on the typical test system and simulation results are derived. The conclusions are drawn in section 5.

2. Problem formulation

2.1. General architecture of microgrid under study

The microgrid under study includes loads, local generation resources, and energy storage systems. Loads in microgrids also can be divided into two main groups: adjustable loads and fixed loads. Adjustable loads can be controlled by operators and can be shifted or curtailed whole or part of them when it's necessary from a microgrids operator point of view. In contrast, fixed loads cannot be controlled or shifted by the operator and he doesn't have any control over these loads and they must be supplied under all conditions. Power generation resources in microgrids are classified into two main categories. The first group includes dispatchable resources whose output power can be controlled by system operators. Microgrid operators can control the output of dispatchable resources and the amount of power they generate. On the other hand, generated power of non-dispatchable resources could not be under control and depended on factors out of control. In this paper, photovoltaic cells and wind turbines are considered non-dispatchable power resources and Microturbines acted as dispatchable ones. A schematic diagram of a typical microgrid under study is depicted in Fig. 1.

Microgrids can operate in two different modes: islanding mode and grid-connected mode. In grid-connected mode, ESSs store energy in low-price periods and give back that energy to the microgrid during the high-price time. In this mode, the microgrid can supply its consumers with energy they import from the main grid. Microgrid operation is based on the assumption that they must satisfy their load with minimum cost and maximum reliability at all times. In disturbances, a microgrid must be able to isolate itself from the main grid and meet its load requirements with help of its resources. ESSs play an important role in islanding mode to satisfy more loads and increase the reliability of microgrids.

2.2. Microgrid modelling

In this section, the optimal scheduling of ESSs in microgrids constrained to reliability requirements is presented. Two objective functions are used in this study, where minimizing microgrid costs and Energy not supplied are considered to fulfill the economic and reliability requirements of microgrids. To have an accurate and acceptable analysis of microgrid operation it is necessary to precisely model the problem parameters.

In the proposed method, the uncertainty of network parameters such as load, energy price, and the failure rate of microgrid equipment such as lines and substations has been considered. First, according to Monte Carlo Simulation (MCS), some scenarios have been generated. In each scenario, parameter values are selected randomly based on their mean and standard deviation values. Then after the generation of sufficient scenarios, a proper scenario reduction technique is applied to reduce the number of scenarios to acceptable sets.

2.2.1. ESS modeling

ESS units, in general, are modeled by their characteristic properties such as power and energy capacity, location, charging and discharging cycles, and implementation requirements. Their main limitations are maximum and minimum state of charge (SOC); charging and discharging efficiency and ESS charging/discharging power limitation.

The two main parameters of ESSs are rated capacity and rated power. Rated power will determine the energy charging/ discharging rate of storage energy systems. On the other hand, rated capacity is the amount of energy that a storage system can store. High-capacity ESSs are capable to store high power but they don't have efficient charging-discharging power. On contrary, low-capacity ESSs have suitable charging/ discharging power. State of Charge (SOC) of ESS is expressed as a percentage of energy that is available at time t Eq (1):

$$SOC(t) = \frac{E(t)}{E_n} \tag{1}$$

SOC is the state of charge of ESS and it changes during charging/ discharging process. The amount of SOC will increase when the ESS charging and it will decrease when ESS discharging. Instead of SOC sometimes the energy of ESS is expressed as the depth of discharge (DOD). It is defined as an amount of energy (charge) that is eliminated at a given time. It determines the total amount of charge that can be stored in the battery at a certain state and is expressed in Eq. (2).

$$DoD(t) = 1 - SOC(t) \tag{2}$$

ESS can operate in three different modes: charging, discharging, and idle. The SoC of ESS unit during discharging and charging of the battery is respectively defined as Eqs. (3) and (4). In Charging mode, SOC of battery depends on battery charging efficiency (η_{ch}), battery charging power (P^{ch}) and battery self-discharge rate (ζ).

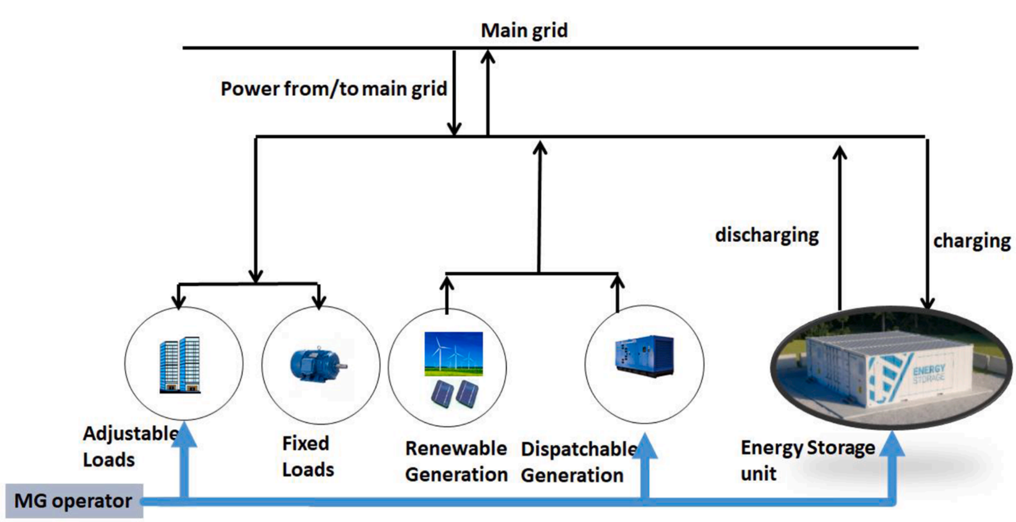

Fig. 1. the schematic diagram of the structure of Microgrid understudy.

$$SOC(t+\Delta t) = SOC(t)(1-\zeta) + k.P_{ESS}^{disc}.\frac{\Delta t}{\eta_{disc}.C_{ESS}} \tag{3}$$

$$SOC(t+\Delta t) = SOC(t)(1-\zeta) + k.\left(\eta_{ch}.P_{ESS}^{ch}\right).\frac{\Delta t}{C_{ESS}} \tag{4}$$

ESS installation imposes huge costs on microgrids. Therefore, from both economic and security viewpoints, an accurate and practical ESS cost model would enhance the modeling of system operation. In order to schedule ESS operation, it is essential to obtain the exact ESS cost model. ESS cost is composed of ESS capital cost and ESS operation cost. Batteries don't use any fuel, thus their operation cost is mainly due to their degradation and their aging cost.

The aging cost of ESS is correlated with its degradation. ESS degradation depends on cycling and calendar aging of the battery. The cyclic aging comes from the C-rate, temperature, DOD usage, and number of cycles, while calendar aging depends on the SOC, temperature, and time. The ESS aging cost is dependent on the degradation ratio of the life (η_t) and installation cost (IC) as it is shown in Eq. (5):

$$AC_t = \eta_t * IC^{ESS} \tag{5}$$

The aging ratio of battery per cycle can be obtained by the following equation and use for aging cost calculation. Aging cost will be added to cost minimization problem. [35]

$$\eta_t = \frac{0.5}{NC_t^{ESS}\left(S_t^{SW}, S_t^{Avg}\right)} \tag{6}$$

In this equation aging ratio is related to number of cycles (NC) which is function of both average SOC level and changes of SOC during one cycle.

2.2.2. Wind power modeling

Generated power of wind turbines is dependent on wind velocity modeling of wind power should perform considering its forecast uncertainties. Previous studies have shown that wind speed can be successfully modeled by Weibull distribution:

$$f(v) = \left(\frac{k}{\gamma}\right)\left(\frac{v}{\gamma}\right)^{k-1} e^{\left(\frac{v}{\gamma}\right)^{k}} \tag{7}$$

When the cut-in wind speed is reached, the turbine starts to produce its power. As the wind speed increases, the turbine output will also increase. When the wind speed is too high, to protect the turbine, the turbine equipment will be automatically removed. Therefore, the output power of the turbine can generally be expressed by a piecewise function, as shown in Eq. (8). Output power of wind turbines in terms of their wind speed is dependent on the wind turbine characteristic curve and is given by the following equation:

$$p = \begin{cases} 0 & 0 \le SW_t \le V_{ci} \\ \left(A + B * SW_t + C * SW_t^2\right) * P_r & V_{ci} \le SW_t \le V_r \\ P_r & V_r \le SW_t \le V_{co} \\ 0 & V_{co} \le SW_t \end{cases} \tag{8}$$

Where P is generated power of wind turbine and A, B, and C are shape parameters of WT. Fig. 2 demonstrates the typical power curve of the wind turbine generator.

A two-state up and down Markov model is used as the probabilistic model to demonstrate wind turbines in reliability studies. In this model availability of WTG with probability equals 1-q_{WTS} and rated capacity of $p_{WTS.rated}$, or unavailable with probability equals to q_{WTS}. q_{WTS} is defined as follows:

$$q_{WTS} = \frac{MTTR_{WTS}}{MTTF_{WTS} + MTTR_{WTS}} \tag{9}$$

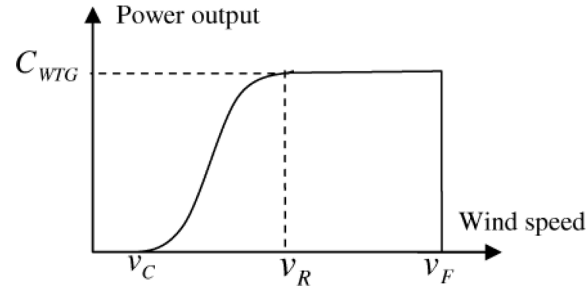

Fig. 2. Power output of wind turbine generator.

2.2.3. Solar power modeling

The generation of solar power systems depends on solar irradiance and solar cells features and ambient temperature. Reference [36] compared different probability density distributions with random behavior of solar irradiance and result that Beta pdf could be used to model the solar irradiance well. Thus, in this paper the beta distribution is used to show the uncertainty of solar irradiance as follows:

$$f(v) = \left(\frac{2v}{c^2}\right)\exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{10}$$

When solar irradiance is known, generated power of PV cell will obtain by the Eq. (11). In this equation, generated power of photovoltaic cell (P_{pv}) is related to forecast solar radiation (G_t) and the certain radiation point (R_c).

$$P_{pv} = \begin{cases} \frac{\eta_c}{K_c}(G_t)^2 & 0 < G_t < R_c \\ \eta_c G_t & G_t > R_c \end{cases} \tag{11}$$

As for wind power, the reliability of solar power is modeled with two-state markov model:

$$q_{PVS} = \frac{MTTR_{PVS}}{MTTF_{PVS} + MTTR_{PVS}} \tag{12}$$

2.2.4. Load modeling

Microgrid load consumption is affected by its consumer type and depends on the day of the week, the week of the month, and the month of the year. The probabilistic behavior of microgrid load is modeled by normal distribution function as follows:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\alpha}\right)^2} \tag{13}$$

3. The proposed method

Some objectives are conflicting and it is necessary to make a trade-off between them. Multi-objective algorithms can act efficiently with problems with conflicting or mathematically unrelated objective functions. In the proposed method first, some scenarios are generated based on standard deviation and mean value of equipment and their probability distribution factor as explained in the previous section. Then scenarios will reduce to accelerate the speed of the method.

3.1. Objective functions

3.1.1. Cost objective function

The first objective function of the proposed algorithm is cost minimization of the microgrid. Microgrid costs consist of operation cost (OC) as well as aging cost (AC) and can be formulated as follows:

$$\min Cost_t = OC + AC \tag{14}$$

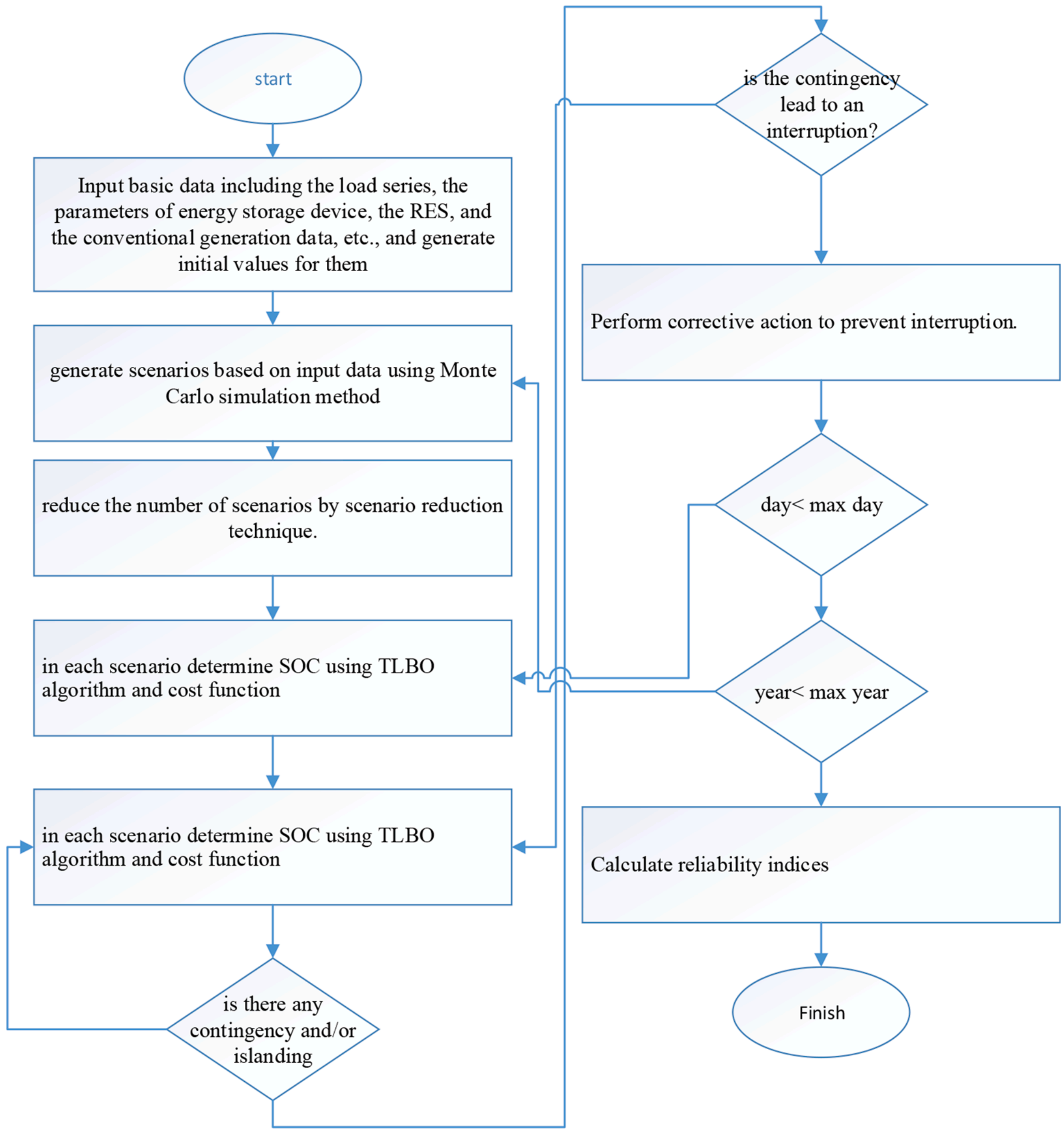

Fig. 3. Flowchart of proposed method.

$$OC_{s,t} = \sum_{i=1}^{N_S} \left(P_{ESSi} * \text{cost}_{ESS,i}\right) + \sum_{i=1}^{N_{RES}} \left(P_{RES,i} * \text{cost}_{RES,i}\right) + \sum_{i=1}^{N_{dg}} F_{dg,i}\left(P_{dg,i}\right) + P_{grid} * \text{cost}_{grid} \tag{15}$$

Operation cost includes all the possible scenarios of load and renewable energies power output (15). The first term in the operation cost function corresponds to the cost of ESS units and the second term shows the cost of renewable energy resources. The operation cost of dispatchable units is represented in the third term. Finally, the last expression models power imported from (exported to) the main grid to (from) the microgrid. Therefore the objective function for the cost of the microgrid will be as follows:

$$\text{minCost}_t = \sum_{i=1}^{N_S} \left(P_{Si} * \text{cost}_{ESS,i}\right) + \sum_{i=1}^{N_{RES}} \left(P_{RES,i} * \text{cost}_{RES,i}\right) + \sum_{i=1}^{N_{dg}} F_{dg,i}\left(P_{dg,i}\right) + P_{grid} * \text{cost}_{grid} + AC_t \tag{16}$$

3.1.2. Reliability objective function

One of the main purposes of microgrid scheduling is reliability enhancement, but it is considered simultaneously with cost minimization. Energy Not Supplied (ENS) has been chosen as an objective and objective function can be obtained by (17):

$$ENS = \sum_{i=1}^{N_{\text{inter}}} L_i \text{Pr}_i \tag{17}$$

3.2. Constraints

All variables must be within their boundaries. Constraints of the suggested optimization problem are listed as follows:

3.2.1. ESS constraints

There are some limitations on the charge and discharge rate of storage devices during each time interval, the following equation and constraints can be considered:

$$P_{ESS}^{sch} < P_{ESS,\max}^{sch} \tag{18}$$

$$P_{ESS}^{disc} < P_{ESS,\max}^{disc} \tag{19}$$

$$SOC^{\min} < SOC(t) < SOC^{\max} \tag{20}$$

Eqs. (18) and (19) specify that the charging and discharging rate of ESSs don't exceed their limitations. To have high efficiency, the State of Charge of the battery should be in predefined ranges. Constraint (20) ensures that the SOC of ESS doesn't exceed its boundaries. During the discharging period, SoC must not go below the SoC_{min} and in charging mode it must not go upper than SOC_{max}.

3.2.2. Renewable energy resources constraints

Output power of renewable energies (PV units and wind turbines) are limited by their maximum power that they can produce. Eqs. (21) and (22) present PV and wind turbine limitations respectively. Constraint in Eq. (21) ensure that PV generated power is lower than PV maximum power and Eq. (22) confirm that wind power doesn't exceed its maximum.

$$0 < P_{PV}^{i} < P_{PV,\max}^{i} \tag{21}$$

$$0 < P_{wind}^{i} < P_{wind,\max}^{i} \tag{22}$$

3.2.3. The balance between load and generation

It is necessary to exist a balance between load and generation in the microgrid and powers generated by microgrid resources can meet the demand of microgrid consumers. If resources could not satisfy the load in a microgrid, the main grid can provide loads for a microgrid. In the grid-connected mode, the microgrid can send or receive electrical energy from the main grid and other microgrids. If available resources in the microgrid can't generate enough power to meet microgrid demands, load shedding must be applied to maintain microgrid stability. Load and generation balance limitation is expressed in Eq. (23):

$$P_S + P_{DG} + P_{RES} + P_{Grid} = P_{load} \tag{23}$$

3.3. Dispatchable units' constraints

Dispatchable DG units have startup and shutdown times that must be considered in the computations. They also have limitations such as Min-max capacity and ramp-up rates. Eqs. (24)-(28) demonstrate these limitations:

$$P_{DG}^{\min} < P_{DG} < P_{DG}^{\max} \tag{24}$$

$$P_{DG,t}^{i} - P_{DG,t-1}^{i} < UR_{DG} \tag{25}$$

$$P_{DG,t-1}^{i} - P_{DG,t}^{i} < DR_{DG} \tag{26}$$

$$SU_{DG,t} > CU(I_{DG,t} - I_{DG,t}) \tag{27}$$

$$SD_{DG,t} > CD(I_{DG,t} - I_{DG,t}) \tag{28}$$

Eq. (24) ensures that generated power of DG is between its maximum and minimum allowable amount. Ramp up and down rate of DG impose some restrictions on its operation that expressed in equations(25) and (26). Start-up and shot-down costs are calculated based on cost constants and their operating time. Eqs. (27)-(28) show these calculations.

3.4. Optimization method

The optimization problem described in the previous sections is in MINLP format. Here, we employ the TLBO algorithm to obtain optimal solutions. TLBO is an effective and fast evolutionary algorithm that is inspired by a learning mechanism in a class [37]. In the algorithm, the population is assumed to be learners of a class. The general process of TLBO is divided into two main phases: teacher phase and learner phase. Teacher is considered as best solution obtained so far. Learners can enhance their knowledge by either learning from teacher or by learning through the interactions between themselves. In teacher phase, a good teacher brings up knowledge of students and improves the mean of class (Eq. (29)). In learner's interaction between students in class can enhance their knowledge (Eq. (30)). The students can also gain knowledge by discussing and interacting with other students. Students can enhance their knowledge if the other students have more knowledge about that subject.

$$X_{inew} = X_i + r\left(X_i^{best} - Tf * M_i\right) \tag{29}$$

$$X_{inew} = X_i + r\left(X_j - X_i\right) \tag{30}$$

$$X_{inew} = X_i + r\left(X_j - X_i\right) \tag{31}$$

There are two approaches to adding reliability to the optimization problem: The first approach is to add reliability to the objective function that was considered before. The other approach is to use a multi-objective optimization problem. In the second approach, we had a front of non-dominated solutions instead of a single solution.

3.5. Operation strategies

Microgrid operation is scheduled based on different horizons and various strategies. In this paper, we develop a method to schedule ESS and microgrid in both daily and weekly mode time horizons. The scheduling method regarded reliability and cost-driven operating strategies.

A Daily mode: In daily mode, the ESS operate on a daily basis and energy output of ESS must be same at the beginning and end of day. In other words, net change of energy in ESS in a day must be equal to zero. ESS will operate in day-ahead power market and all variables must be forecasted for next day.
B Weekly mode: In weekly mode, energy output of must be same at the beginning and end of week. In this strategy, SOC is not forced to be same at the end and beginning of each day, and continuity between days is acceptable in this mode. Therefore, it can use in operating methods which need less charging/discharging cycles.

In cost-driven operation strategy, overall system operating costs are chosen to enhance through energy arbitrage. In this strategy ESS save MG extra energy in non-peak hours and fulfill load demand in peak hours that market price is higher.

In reliability-driven mode, it is essential to maintain system adequacy level in certain level even in islanding operation. So, the main goal of this strategy is satisfying system load demand.

If ESS is used for reliability enhancing, its SoC must be at higher levels. On the other hand, in cost-driven mode ESS can discharge to the lower levels to satisfy more loads in peak hour (when price is higher). This strategy would lead to the larger amount of Depth of discharge if ESS aging cost does not involved in scheduling plan.

It is assumed that in grid-connected mode, microgrid's power demand can completely supplied by the main grid and therefore there would not be any load interruption in that mode and adequacy assessment of generating units does not calculate. In contrast, in the islanding mode, reliability concerns (adequacy and security) are of high importance. While MG operates in islanding mode ESS activity would become more important because main grid can't supply energy and the whole load must be supplied by generation and ESS units in MG. Hence, ESS will operate in reliability-driven mode in this situation.

3.6. The proposed algorithm

The proposed algorithm is a optimization approach based on

Teaching-Learning Based Optimization algorithm. The algorithm for solving formulated optimization problem described before is represented as follows:

In the proposed method charging/discharging status of ESS is selected as decision variables. Different scenarios are generated based on input data using MCS method. In this section, for each hour forecasted value of each parameter is calculated by standard deviation and mean of that parameter and its probability distribution function. Based on the generated scenarios of charging/discharging schedule, a probabilistic optimization problem is solved and MG's operation cost will be calculated. In each hour, probabilistic TLBO-based optimization algorithm is used to determine charging behavior and SOC of ESS in the microgrid. This optimization in the normal operation is performed just by cost function. When the optimal scheduling of DERs and power flow in different scenarios are obtained, the ENS can be calculated. For calculating ENS in each islanding scenario, the amount of energy not supplied is calculated.

4. Case study

The proposed formulation has been implemented on IEEE 33 bus standard test system[38]. The original test system is supplied just with the main grid. This test system is modified and add some DGs, RESs, and ESSs to become suitable for studying scheduling problem. Fig. 4 demonstrates a schematic diagram of this network. Also, a daily time horizon consisting of 24-h periods is considered for DM and 168-h for weekly mode scheduling.

A new method based on TLBO has been used for minimizing cost of Energy in the microgrids. To test the proposed method we choose a standard system to show the performance of the method. In each hour SOC of ESS will be determined based on load level and consumer requirements. Choosing an operation mode strategy can influence the scheduling of Energy Storage system charging/discharging behavior. The characteristic of DERs used in the simulation is presented in Table 1. It is noteworthy that the output power of PV and WTG in each hour is equal to the product of their capacity to its power daily curve, which is depicted in Fig. 2. ESS technology used as a test case in this study is

The FOR of network equipment is assumed to be 0.1 (occ/yr) and the failure rate of equipment is 10 days/year. Islanding duration is assumed to have normal distribution function with mean of 5 h and standard deviation of one hour [38]. It is also assumed that the investment cost of ESS is 200,000 $. Finally, the standard deviation of uncertain parameters is set at 10% and MCS generates 1000 scenario at first and then reduce them to 100 scenarios.

Forecasted load and renewable energy output for a day and one are illustrated in Fig. 5. These data are used in daily and weekly mode scheduling.

The proposed method is coded in MATLAB 2018a software and the numerical results are derived as follows:

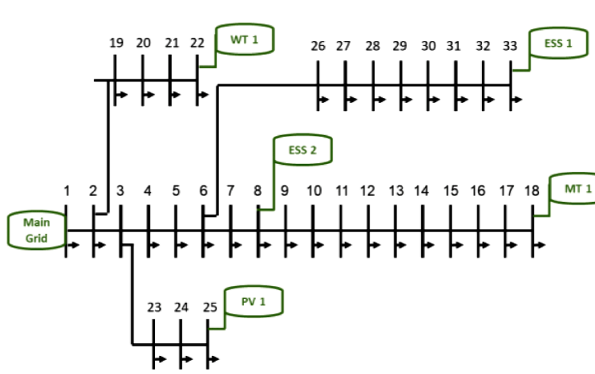

Fig. 4. Modified 33 bus system.

Table 1
DGs characteristic [17].

Type	Operation cost	Min max capacity	Ramp Up/down
MT	51.86	0–0.12	0.06

Table 2
The hourly electricity price in the open market [39].

Hour	Price	Hour	Price
1	0.033	13	0.215
2	0.027	14	0.572
3	0.020	15	0.286
4	0.017	16	0.279
5	0.017	17	0.086
6	0.017	18	0.059
7	0.033	19	0.050
8	0.054	20	0.061
9	0.215	21	0.181
10	0.572	22	0.077
11	0.572	23	0.043
12	0.572	24	0.037

4.1. *Scheduling results of energy storage systems in the microgrid*

Scheduling of Energy storage has been performed based on the proposed method and the results are illustrated in Table 3. For evaluating the effectiveness of the proposed method both daily mode (DM) and weekly mode (WM). Referring to this table, the highest SOC of ESS is at 6:00 and the lowest SOC is at 19:00.

The charging/discharging process of ESS in weekly mode scheduling is shown in Fig. 6 and Fig. 7. The average SoC is higher in WM scheduling so the average DOD is lower than DM which can help to prevent battery wearing out. On two days of week, energy storage capacity stays constant and it doesn't use for all day long because of its operation cost (aging cost).

4.2. *Assessing the ability of the proposed method*

The results from the proposed algorithm for reliability and cost data are presented in Table 4. The problem solved by TLBO and it is compared with other Solvers in order to see the efficiency of proposed method. This results confirms the ability of suggested method to determine operation scheduling of ESS in MGs.

4.3. *Evaluating reliability indices of microgrids*

Reliability of microgrids can be calculated based on the proposed methodology. To demonstrate the effectiveness of the proposed method 4 different cases are deployed in the test system. In each scenario, both islanding and grid-connected modes are taken into consideration in 168 h scheduling horizons.

Case 1: ESS scheduling daily mode-cost minimization
Case 2: ESS scheduling daily mode-reliability enhancement
Case 3: ESS scheduling weekly mode-cost minimization
Case 4: ESS scheduling weekly mode- reliability-driven mode

The proposed algorithm is all four cases has been performed and the obtained results is presented in Fig. 8.

At first in case 1, between 00:00 and 5:00 in the morning battery will be charged because energy price is low. Then between 5 and 17, the battery will remain in idle form and energy will import from the main grid if the microgrid generation units couldn't satisfy load. At the end of the day, in peak hours between 17 and 00 battery energy is discharged because the electric price is high and it's better to not receive energy from the main grid. Case 2 is based on reliability enhancement so ESS

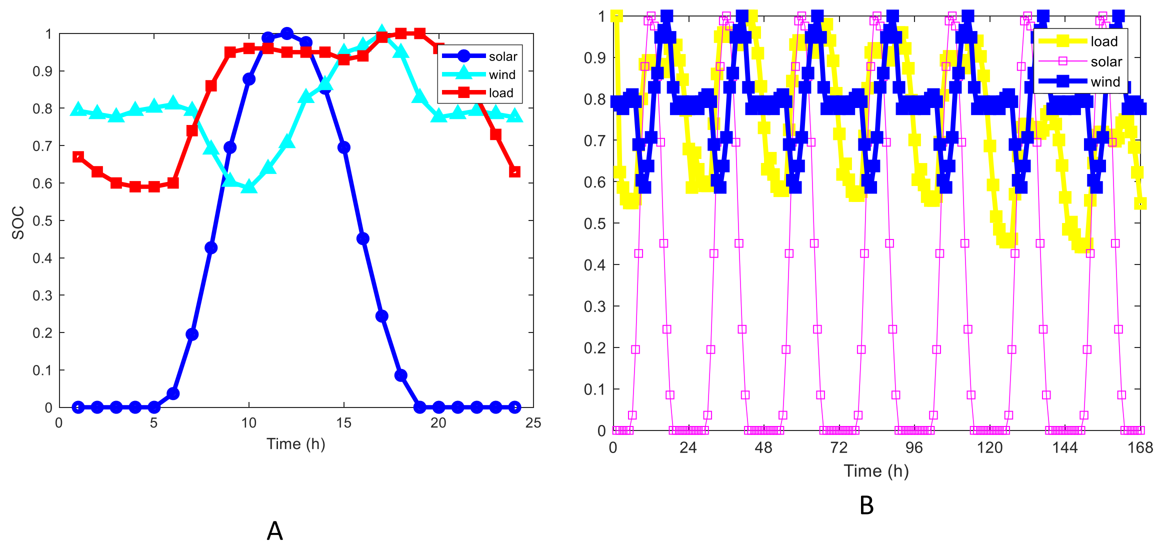

Fig. 5. forecasted value of load and renewable energy for a day (a) and a week (b).

Table 3
Scheduling of ESS in DM scheduling strategy.

hour	SoC	Hour	SoC	Hour	SoC	Hour	SoC
1	0.2	7	0.6	13	0.5	19	0.6
2	0.4	8	0.5	14	0.6	20	0.6
3	0.6	9	0.5	15	0.7	21	0.4
4	0.6	10	0.5	16	0.7	22	0.3
5	0.6	11	0.5	17	0.75	23	0.2
6	0.7	12	0.6	18	0.68	24	0

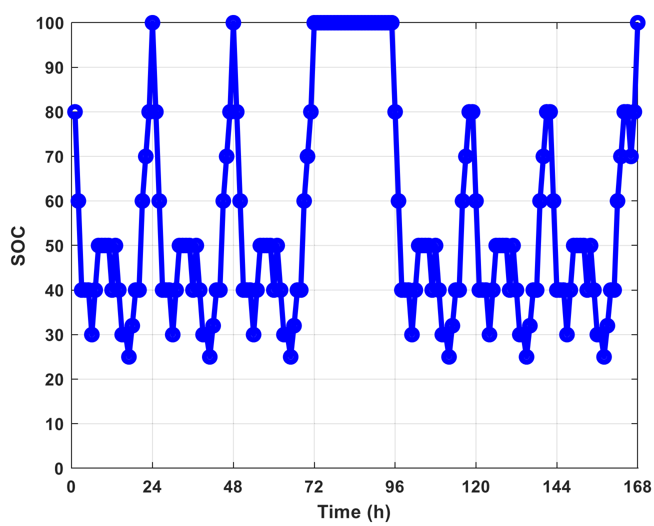

Fig. 6. Soc scheduling of ESS in a weekly mode (WM).

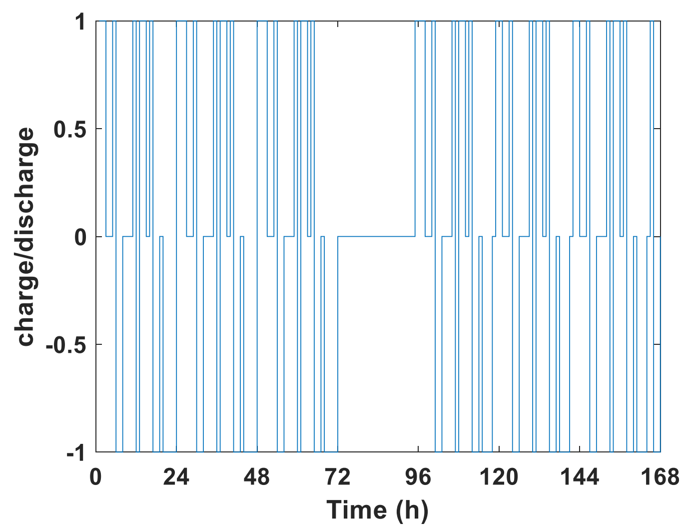

Fig. 7. Charging status of ESS in WM.

Table 4
Result of different algorithms.

Solver	OC	EENS
PSO	639.5	7.17
GA	651.5	6.9
TLBO	602.4	6.84

will charge at 00 to 5 just like case 1. But in the peak hours, it will not be discharged completely because it is necessary to be ready for providing load in islanding situations. In case 3 on the first day of ESS charging strategy battery is charged in 00:00 and 5:00 like in case 1 and in peak hours it will be discharged almost completely but on the 3rd day, because the load is not high in comparison with PV and wind, ESS would not discharge completely. The scheduling process in case 4 shows fewer charge and discharge cycles because operation policy is based on reliability and on all days except for day 1 ESS will remain with high SOC level. In this case, ESS doesn't help microgrid economy.

Operation cost and ENS of each case are illustrated in Figs. 9 and 10 respectively. One can observe in Fig. 10 that weekly mode scheduling has better performance in reliability-driven mode. In case 3 DOD is reduced in comparison with case 1. It is due to the fact that in weekly mode the condition of equal SOC at the beginning of the day is removed. Case 4 has more stable charging state because it is scheduled to be of high capacity in peak hours.

4.4. Effects of different factors on the reliability of microgrid

4.4.1. Influence of parameters of ESS on reliability

In order to assess the effect of ESS scheduling on microgrid operation and reliability, we analyze ESS parameters on the test system. ESS

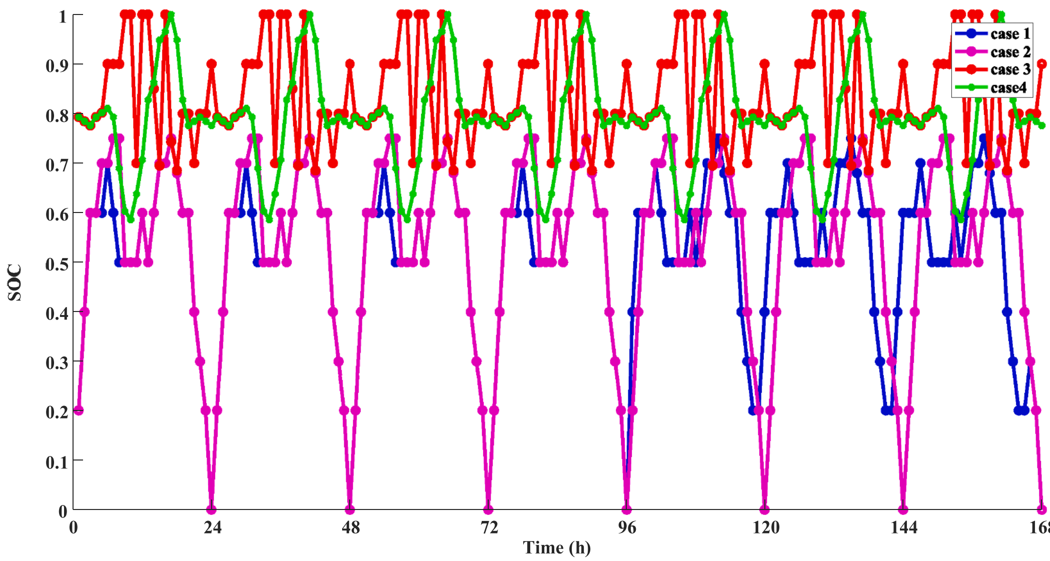

Fig. 8. ESS SOC of different cases in one week.

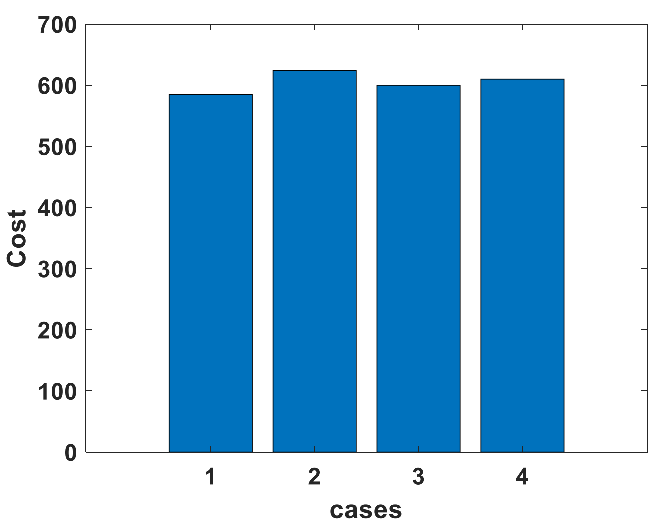

Fig. 9. Operation Cost of scenarios.

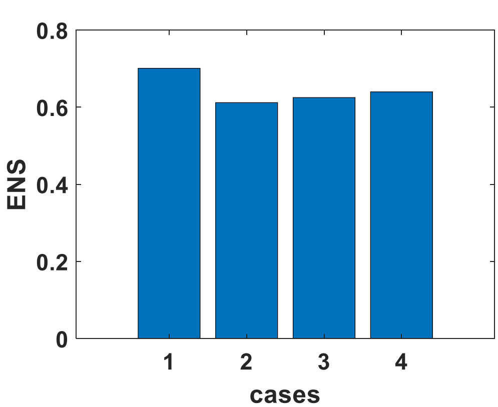

Fig. 10. Energy Not Supplied (ENS) of each cases.

capacity can change its management strategy, therefore figure demonstrates ENS and costs in the operating mode. Higher ESS capacity can reduce the operating cost of MG and also decrease its discharge depth of it. ESS power is also one of the main parameters for enhancing reliability because higher discharge power can be helpful in reliability-driven strategy. It can be observed that EENS value is decreasing as ESS capacity and power are reduced.

4.4.2. *Effect of peak load on reliability*

ESS units are designed to help MGs to decrease operation costs by delivering power to loads during high-price hours or peak hours. But if MG has been forced to work in islanding mode in this period, ESS must provide some part of the load if generated power of RESs and DGs cannot completely satisfy the load requirement. Excessive discharge of ESS and low SOC value may result in load interruption in the microgrid. The effect of the peak load of MG on reliability indices is depicted in Fig. 12. One can observed that in Fig. 12 EENS grows gradually with increasing peak load.

5. Conclusion

This paper presented a probabilistic model for optimal scheduling of energy storage systems in a microgrid based on MCS simulation in both grid-connected and islanding situations and also, modeling the aging cost of ESS units concerning both cycling and calendar factors. We first investigated the scheduling and reliability problems of MGs and the associated constraints. Then we proposed a new technique to schedule ESSs in MGs in both daily and weekly modes. This technique is a multi-objective optimization problem that minimizes costs and enhances the reliability of the microgrid that is solved by the TLBO algorithm. Using the simulation conducted on the modified 33 bus test system, it could be observed that the reliability scheduling of ESS operation in microgrid will help to meet the microgrid requirements more efficiently. Results illustrate this point clearly that charging-discharging of ESS can effectively reduce the cost of microgrids while it can improve reliability performance of the system. The results from daily and weekly mode are compared and the advantages and disadvantages of each mode are discussed. It is observed that aging cost and reliability can enhance by weekly mode scheduling while total cost is better managed in daily mode scheduling. A further study could assess the effects of selecting other types of ESS to determine differences between weekly and daily

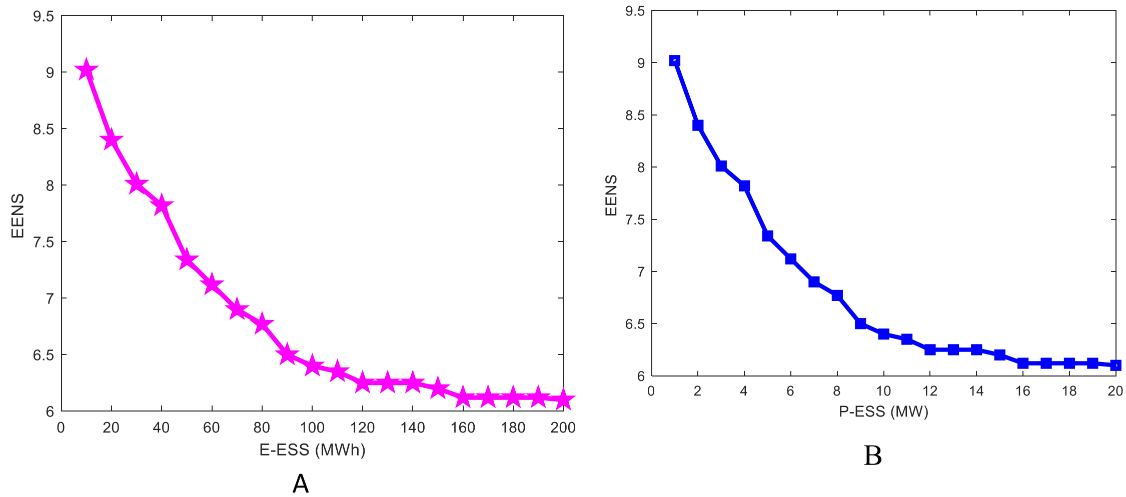

Fig. 11. Effect of ESS capacity (a) and discharge power (b) on EENS.

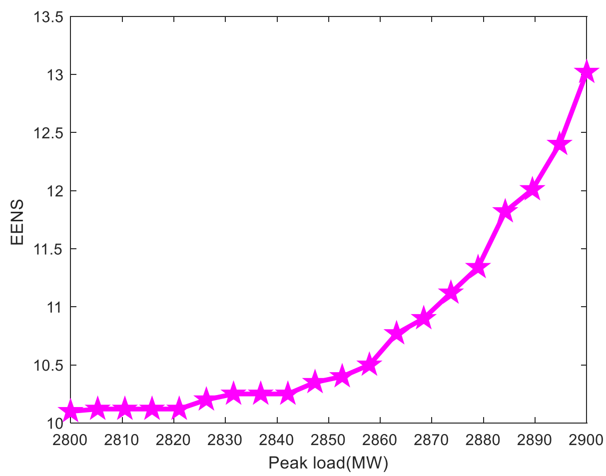

Fig. 12. EENS variations versus Peak Load.

mode operating strategies. Also, further studies need to be carried out in order to determine the impact of ESS scheduling on more reliability indices in microgrid.

CRediT authorship contribution statement

Ehsan Rahmani: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft. **Sirus Mohammadi:** Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft. **Mahmoud Zadehbagheri:** Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft. **Mohammadjavad Kiani:** Investigation, Resources, Conceptualization, Formal analysis, Methodology, Project administration, Software, Supervision, Validation, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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