Stochastic multi-objective model for optimal sizing of energy storage system in a microgrid under demand response program considering reliability: A weighted sum method and fuzzy satisfying approach

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In this paper, a multi-objective optimization model is proposed to calculate best possible size of energy storage system (ESS). The proposed model is solved utilizing weighted sum method. Positive effects of demand response program (DRP) are considered in the proposed paper. By utilizing the weighted sum method, many various solutions are obtained. Then to select the best possible solution, fuzzy satisfying approach is employed. The proposed multi-objective model includes two conflicting objective functions: 1) the first objective function is minimization of microgrid investment cost as well as the operation cost; 2) the second objective function is minimization of loss of load expectation (LOLE). Microgrid includes some local units inside itself which may have some unknown outages and also due to variable and unstable output of renewable units, utilization of ESS is essential to improve stability of microgrid. The i mpact of DRP implementation is evaluated on microgrid related costs and the results are compared to validate the proposed technique. In order to simulate and model the proposed stochastic ESS optimal sizing problem in a microgrid, a mixed-integer program (MIP) is utilized.

keywords: *Energy storage system (ESS), multi-objective optimization model, microgrid, demand response program (DRP), weighted sum method, fuzzy satisfying approach.*

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NOMENCLATURE

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A. Indices:

S Scenario index

t Day index

r Renewable unit index

h Time period index

n Unit index

B. Parameters:

ICP_B Installation cost of power rating for energy storage system (ESS)

ICE_B Installation cost of energy rating for ESS

ρ_s scenario possibility

ρ_t Electricity price

$P_M^{\max}$ Maximum limitation of power import (export)

$P_i^{\min}$ Lowest amount of thermal unit output

$P_i^{\max}$ Highest amount of thermal unit output

UX_{ith}^s Outage condition of unit

DR_i Ramp down rate of unit

UT_i Minimal up time for unit

DT_i Minimal down time for unit

$P_{W,th}^s$ Production of wind turbine

P_B^r Rated power of ESS

k Extent of discharge

Δ_t Time pause

C^0 Amount of charge at the start of every day

C^{end} Amount of charge at the end of every day

CIF_B Main investment budget of ESS

$LOLE^{target}$ Predicted value for loss of load expectation

$P^s_{D,th}$ Load supplied by microgrid

DRP^{max} Maximum value of demand response program (DRP)

NG Available conventional units number

NR Available renewable units number

NH Considered hours number

NT Considered days number

C. Variables:

IC Microgrid overall investment cost

OC Overall operating cost of microgrid

CB^{max} Maximum charge limitation of ESS

F_i Function of generation cost for unit

P^s_{ith} Produced power by thermal unit

I^s_{ith} Unit engagement condition

SU^s_{ith} Startup cost of thermal unit

$P^s_{M,th}$ Sold (purchased) power to (from) the main grid

$P^s_{r,th}$ Produced power by renewable unit

$P^s_{b,th}$ ESS energy consumption (production)

LS^s_{th} Load shedding

$P^s_{DRP,th}$ Microgrid new load considering DRP

$UY^s_{M,th}$ Outage condition of line connecting upstream grid to the microgrid

UR_i Ramp up rate for thermal unit

y^s_{ith} Binary variable, 1 if unit is started up; otherwise 0

z^s_{ith} Binary variable, 1 if unit is shut down; otherwise 0

$I^s_{it(h-1)}$ Unit commitment condition

C^s_{th} ESS condition of charge

C^s_{t1} ESS condition of charge at the start of every day

W^s_{th} Binary variable for load shedding modeling

$LOLE$ Loss of load expectation

TOU^s_{th} Microgrid new load considering time-f-use program (TOU)

1. INTRODUCTION

Utilization of energy storage system (ESS) in power networks has many advantages. As mentioned before, renewable units may not have a stable output due to their specific nature. Therefore, ESS can be used to solve this problem and provide a reliable generation and improve peak load management. So, in addition to ESS utilization in microgrid, best possible size of the ESS should be determined [1–3].

A. Literature review

In comparison with the power system, microgrid is a small-scale distribution system which contains many various loads and different kinds of units (thermal and renewable) for supplying loads. Microgrid and upstream grid can be linked to each other through a line by which microgrid would be able to sell (purchase) energy to (from) the upstream grid. In order to improve microgrid reliability and solve the related problems, utilization of ESS is necessary and optimal size of ESS should be determined to minimize total cost as well as loss of load expectation (LOLE) [4].

Due to variable and unstable output of renewable units, ESS is utilized as an extra energy source besides wind turbine and photovoltaic system to soften produced power [5–7]. In order to optimally size ESS with considering reliability citation, an analytical method has been implemented in [8]. In [9], applications and future of ESS have been studied. In [10], ESS optimal size has been found to manage peak hour consumption. Also in [11], a storage system for power control and management applications has been investigated. Genetic algorithm has been employed to optimally size energy storage system in [12]. Using an alternative direction method of multipliers, energy storage system is optimally sited and sized in [13]. Optimal capacity and location of battery energy storage system has been found using a heuristic method in [14].

Optimal operation of a grid-connected battery-PV system has been investigated in [15] in which optimal size of battery storage is determined. With the aim of minimizing total operational cost of an on-grid microgrid, a new energy management technique, including economic strategies for operation of system and sizing of battery storage has been presented in [16]. With the aim of minimizing total cost and reducing total emission as well as increasing the life cycle, a battery-PV-wind-diesel hybrid energy system has been optimally sized and allocated in [17]. In order to minimize power losses in electrical distribution networks, battery storage system has been employed and optimally sized in [18]. Due to the intermittent output photovoltaic system, energy storage system has been utilized and optimally allocated in [19]. Optimal allocation of energy storage in power system has been evaluated from an economic view point in [20]. In order to control fluctuating generation of renewable energy resources like photovoltaic system, a bi-level optimization technique based on genetic algorithm has been proposed to optimally site and size the battery energy storage system in [21].

Furthermore, electrical loads can participate in DRP to reduce their operational costs. Participating in DRP, customers are responsible to change their energy consumption pattern to reduce their expenses. On the other hand, consumers get incentives or they pay less to the utility as they reduce their consumption. Demand response programs are divided into two groups: Incentive-Based Programs (IBPs) and. IBPs are divided into market-based programs and classical programs. In these programs, customers get incentives as much as they reduce their consumption.

In PBPs, dynamic pricing rates, including Time of Use (TOU) rate, Critical Peak Pricing (CPP), Extreme Day Pricing (EDP), Extreme Day CPP (ED-CPP) and Real Time Pricing (RTP) are utilized.

B. Novelty and contributions of this research

Difference of this paper from other works is the method used for solving the problem. In this paper, we have utilized weighted sum approach to solve the proposed multi-objective model with demand response program (DRP) consideration. The main objective of the proposed model is to minimize microgrid investment cost as well as the operation cost and minimize LOLE. Uncertainty modeling of system component outages, microgrid load and generation of renewable sources have been considered in the proposed paper. In the proposed paper is time-of-use (TOU) of DRP which is employed to manage microgrid load and transfer some percent of load from peak time (expensive) periods to another time (cheaper) periods to soften the load curve which leads to total cost minimization. Two different states (with and without DRP) have been studied and the results are compared to show the effects of DRP implementation. Finally, to formulate the proposed model for the ESS optimal sizing problem with considering DRP, a mixed-integer programming (MIP) is utilized. Based on the explanations given above, contributions and novelty of proposed paper are presented as follows:

1. Multi-objective optimization model to minimize total cost as well as LOLE and to provide a win-win strategy for both sides (cost and LOLE).

2. Pareto front is obtained for both conflicting objective functions and trade-off solution is selected.

3. Loads have been enabled to participate in DRP to reduce their cost by changing their energy consumption pattern.

C. Organization of proposed paper

The rest of the proposed paper is classified as follows: The problem is mathematically studied in detail in section 2. Techniques and methods, (weighted sum and fuzzy satisfying approach) used for solving multi-objective model, are explained in section 3. 2 case studies are studied in Section 4 to show the impact of DRP. Finally, conclusions are presented in Section 5.

2. PROBLEM FORMULATION

The main purpose of the proposed paper is to find optimal size of ESS in which total cost as well as LOLE is minimized. So, as the first objective function, total cost of microgrid containing investment cost of ESS and operation cost of microgrid should be minimized. For more clarification, we can divide microgrid operation cost into three individual costs, including the cost related to local units which use energy to produce electricity, the cost that microgrid is faced at the times it attempts to buy electricity from upstream grid and the cost that microgrid pays as local units attempt to start up and shut down. Minimization of LOLE is considered to be the second objective function of the proposed paper. So, in order to solve the proposed multi-objective model, a weighted sum approach, providing a win-win strategy for both sides (total cost and LOLE) is utilized and finally optimal Pareto is achieved.

A. Cost function

As the first objective function of proposed multi-objective model, total cost, including investment cost of ESS and operation cost of microgrid should be minimized (1).

$$Min\Phi 1 = IC + OC \tag{1}$$

$$IC = ICP_B P_B^R + ICE_B C_B^{\max} \tag{2}$$

$$OC = \sum_{s=1}^{Ns} \rho_s \sum_{t=1}^{Nt} \sum_{h=1}^{Nh} \sum_{i=1}^{Ng} \left[F_i \left(P_{ith}^s \right) I_{ith}^s + SU_{ith}^s \right] + \sum_{s=1}^{Ns} P_s \sum_{t=1}^{Nt} \sum_{h=1}^{Nh} \lambda_{th} P_{M,th}^s \tag{3}$$

It should be noted that the main goal of proposed work is to determine an optimal size for ESS in which total cost as well as LOLE is minimized. Equation (1) expresses that ESS investment cost and microgrid operation cost should be minimized. In equation (2), ESS investment cost has been divided into two separate costs: power rating cost and energy rating investment cost. Variable and permanent costs are also added to the power rating cost. Considered costs are calculated on a yearly premise and by finding optimal size of ESS, operation cost of ESS will be decreased [22]. Microgrid operating cost is the sum of three separate costs: The cost related to local units which need energy to produce electricity, the cost that microgrid is faced at the times it attempts to buy (sell) electricity from (to) the upstream grid and the costs that microgrid pays as local units attempt to start up and shut down (3).

B. Reliability function

As the second objective function of proposed multi-objective model, LOLE should be minimized (4).

$$Min\Phi 2 = LOLE = \sum_{s=1}^{N_S} \rho_s \sum_{t=1}^{N_T} \sum_{h=1}^{N_h} w_{th}^s \tag{4}$$

$$0 \leq LS_{th}^s \leq M.w_{th}^s \tag{5}$$

Equation (4) shows possibility of each scenario in LOLE which expresses load curtailment. In order to express the amount of load curtailment at each scenario and time, equation (5) is utilized. If load decreases, w_{th}^s will be 1.

C. Microgrid and unit limitations

As shown in equation (6), the amount of the produced energy should be equal to the amount of energy demand with DRP consideration. It means that microgrid production (production of thermal and renewable units) plus the energy that upstream grid sells (buys) to (from) the microgrid should be equal to energy demand with DRP consideration. At the times that energy demand is more than microgrid production, we may have load shortage. So, to show and express this shortage, a variable called LS_{th}^s is added to the equation (6). If ESS starts charging, $P_{B,th}^s$ will be considered negative and $P_{B,th}^s$ will be considered positive if it starts discharging and it will be zero if it does not attempt to charge or discharge. If upstream grid sells power to the microgrid, upper grid power will be considered positive and it will be considered negative if upstream grid purchases energy from microgrid and it will be considered zero if microgrid does not attempt to purchase or sell energy. Equation (7) constrains the maximum power that can be transferred between upstream grid and microgrid. Finally, equation (8) provides load shedding constraint for stable operation.

$$\sum_{i=1}^{N_G} P^s_{ith} I^s_{ith} + \sum_{r=1}^{N_R} P^s_{rth} + P^s_{B,th} + P^s_{M,th} + LS^s_{th} = P^s_{DRP,th} \tag{6}$$

$$\left| P^s_{M,th} \right| \leq P_M^{\max} UY^s_{M,th} \tag{7}$$

$$0 \leq LS^s_{th} \leq P^s_{DRP,th} \tag{8}$$

The limitations related to microgrid thermal units are presented by equations (9)-(13). Equation (9) determines the upper and lower production limitation of thermal unit. The generated energy by thermal unit can only increase or decrease in a predefined period, which is expressed in equations (10) and (11), respectively. Equations (12) and (13) have been used to determine minimal down and up time limitations of local units, respectively.

$$P_i^{\min} I^s_{ith} UX^s_{ith} \leq P^s_{ith} \leq P_i^{\max} I^s_{ith} UX^s_{ith} \tag{9}$$

$$P^s_{ith} - P^s_{it(h-1)} \leq UR_i.(1 - y^s_{ith}) + P_i^{\min} y^s_{ith} \tag{10}$$

$$P^s_{it(h-1)} - P^s_{ith} \leq DR_i.(1 - z^s_{ith}) + P_i^{\min} z^s_{ith} \tag{11}$$

$$\sum_{k=h}^{h+UT_i-1} I^s_{ith} \geq UT_i.y^s_{ith} \tag{12}$$

$$\sum_{k=h}^{h+DT_i-1} (1 - I^s_{ith}) \geq DT_i.z^s_{ith} \tag{13}$$

To show whether to unit is starting up or shutting down, indexes y and z are utilized which determine the limitations (10)-(13). According to the unit commitment in (14)–(15), indexes y and z are determined. If unit attempts to start up, y is 1 and if unit attempts to shut down, z is 1.

$$y^s_{ith} - z^s_{ith} = I^s_{ith} - I^s_{it(h-1)} \tag{14}$$

$$y^s_{ith} + z^s_{ith} \leq 1 \tag{15}$$

In order to solve ESS optimal sizing issue, both thermal and renewable units have been considered in the proposed model. Each renewable unit has an individual production pattern which will be determined by a long-standing estimation. According to [23], to create the production pattern, the power curve of wind turbine should be combined with the input performance of generation unit which can be predicted by a definite approach or simulation method. Weibull probability distribution function can be utilized to model the wind speed dissemination. Based on worthy references [24–26], for prediction of the Weibull parameters, there are many different approaches. Generated power by a wind turbine can be calculated by (16) as follows:

$$P^s_{W,th} = \left\{ \begin{array}{l} 0 \\ \\ \\ V^s_{th} < V_{CI} \\ P_W^{\max} \frac{V^s_{th} - V_{CI}}{V_R - V_{CI}} \\ \\ V_{CI} \leq V^s_{th} < V_R \\ P_W^{\max} \\ \\ \\ V_R \leq V^s_{th} < V_{CO} \\ 0 \\ \\ \\ V^s_{th} > V_{CO} \end{array} \right\} \tag{16}$$

Reliability of microgrid would be challenged due to combination of renewable resources. Since renewable resources size is proportional to the microgrid size, available extra resources plus ESS should supply the energy demand [27].

D. ESS Constraints

Equations (17)–(22) can be used to design ESS.

$$-P_B^R \leq P^s_{B,th} \leq kP_B^R \tag{17}$$

$$C^S_{th} = C^S_{t(h-1)} - P^s_{B,th} \Delta t \tag{18}$$

$$0 \leq C^S_{th} \leq C^{\max} \tag{19}$$

$$C^S_{t1} \leq C^0 \tag{20}$$

$$C^S_{th} = C^{end} \quad ; \quad (h = N_H) \tag{21}$$

$$ICP_B P_B^R + ICE_B C_B^{\max} \leq CIF_B \tag{22}$$

Totally, ESS has three main statuses: useless, charging and discharging. Charging /discharging power is limited by (17). Equation (18) calculates ESS condition of charge and (19) is used to constrain it. The amount of existing energy is equal to the amount we had in previous hour plus the amount we have at the present time. Δt is 1 since time pause is 1 hour. When ESS is charging, P_B^R will be considered negative and it will be considered positive if ESS is discharging. It should be noted that when P_B^R is considered negative, existing energy increases and when P_B^R is considered positive, existing energy decreases. To calculate available energy at the beginning and end of every day, equations (20)–(21) are utilized. ESS installation in power system needs a primary budget, which constraint is expressed by equation (22). So, microgrid size will be limited [28].

Table 1. Probability of scenarios approximated normal distribution function

Scenario number	Value of each relevant scenario	probability of each relevant scenario
S1	$\mu - 2.5\sigma$	0.0123
S2	$\mu - 1.5\sigma$	0.136
S3	μ	0.682
S4	$\mu + 1.5\sigma$	0.136
S5	$\mu + 2.5\sigma$	0.023

E. Demand Response Program

As mentioned before, DRP includes many various programs inside itself and TOU of DRP has been used to reduce total cost of microgrid [29,30]. The reason of DRP implementation is that it can manage and control microgrid load and can transfer some percent of load from peak time (expensive) periods to another time (cheaper) periods to soften the load curve which leads to cost minimization. It should be noted that we can only shift some percentage of load from peak periods to off-peak periods. The mathematical form of the sentence mentioned above is expressed by equation (23).

$$P^{s}_{DRP,th} = P^{s}_{D,th} + TOU^{s}_{th} \tag{23}$$

According to equation (23), the new load with TOU consideration is equal to the amount of primary load plus the variable power, TOU^{s}_{th}. If the load increases, this variable is negative and it is positive if load decreases. It can be seen from equation (23) that due to improvement of intelligent network technology, we can transfer some amount of load from peak periods to off-peak periods. Technical constraints related to DRP are expressed by equations (24) and (25).

$$\left|TOU^{s}_{th}\right| \leq DRP^{\max} \times P^{s}_{D,th} \tag{24}$$

$$\sum_{h=1}^{Nh} TOU^{s}_{th} = 0 \tag{25}$$

As expressed in equation (24), the increasing/decreasing load should not exceed the base load. In the proposed paper, the maximum amount of increasing/decreasing load is considered to be 20 %. Also, equation (25) expresses that the load does not decrease or increase and it is just transferred from peak periods to off-peak periods, which means that the increasing and decreasing loads should be equal during a day.

F. Price and demand uncertainty model

In order to model uncertainty of demand and price, the forecast error distribution curves are divided into some intervals with the width of one standard deviation. In uncertainty modeling, the inputs are the values used for price and demand in deterministic solution. The percentage of increase or decrease in price and demand is considered to be 10%. Fig. 1 shows a sample discrete form of the predication error probability distribution function. It is essential for every available scenario that 2 values be computed:

i. By integrating the area below the probability distribution curve in every period, we can acquire each scenario's probability.

ii. The realized prediction error in each relevant scenario is considered to be the average amount of period. Table 1 shows the amount and its probability in each relevant scenario.

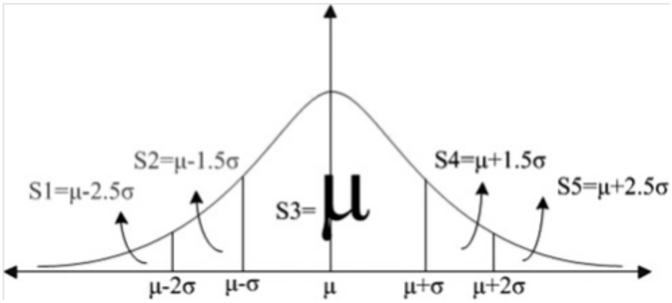

Fig. 1. Probability distribution function for uncertainty parameters

G. Scenario reduction

By utilizing scenario production technique, many various scenarios are acquired. Due to the large size of the obtained scenarios, the proposed model will be complicated and it will take much more time to be solved. So, we need to decrease the number of scenarios. In this paper, the most common probability distance used in stochastic optimization is Kantorovich distance [31], $DK(.)$, defined between two probability distributions Q and Q' by (26), where $c(s,s)$ is a non-negative, continuous, symmetric cost function and the infimum is taken over all joint probability distributions defined on $\Omega \times \Omega$.

$$D_k(Q,Q') = \inf\left\{ \int_{\Omega\times\Omega} c(s,s')\eta(ds,ds') : \int_{\Omega} \eta(.,ds') = Q, \int_{\Omega} \eta(ds,.) = Q' \right\} \tag{26}$$

$$c(s,s') = \left\|s - s'\right\|^{T} \tag{27}$$

The utilized method is the fast-forward algorithm to reduce the number of scenarios [32]. It can be seen from the reported results in [32] that the utilized technique is a popular and particle approach.

3. MULTI-OBJECTIVE SOLUTION METHOD

Multi-objective problems are problems with several objective functions that are usually in conflict with each other and using some special techniques and approaches like weighted sum approach, these problems are solved and Pareto solutions are obtained.

A. Weighted sum approach

In order to solve a problem with objectives more than one, many various approaches are available such as weighted sum approach [33], ϵ-constraint method [34], and evolutionary algorithms [35]. In order to solve the proposed multi-objective model for optimal ESS sizing problem in this paper, the weighted sum approach is utilized. In this approach, different weights are used for conflicting objective functions to generate different Pareto optimal solutions and then different weights select the most satisfactory solution from the optimal Pareto set. In this method, the problem is solved as follows:

$$\min\,[\Phi] = w_1\Phi_1 + w_2\Phi_2 \tag{28}$$

Where

$$w_1 + w_2 = 1 \tag{29}$$

Because of different dimension and range of objective functions (1) and (2), we should normalize both of objective functions. To do this, the fuzzy satisfying technique is utilized.

B. Fuzzy Satisfying Method

As mentioned before, we will have many various solutions in weighted sum approach; therefore, to select the compromise solution amid the obtained solutions, the well-known and popular technique called fuzzy satisfying (or min (max)) approach is utilized. Consider a problem in which N objective functions should be minimized. The fuzzy membership of each objective function maps it to the interval [0, 1]. So the linear membership function for the nth solution of ith objective function is determined as expressed in (30) [36]:

$$\Phi_i^n = \begin{cases} 1 & \Phi_i^n \leq \Phi_i^{\min} \\ \frac{\Phi_i^n - \Phi_i^{\max}}{\Phi_i^{\min} - \Phi_i^{\max}} & \Phi_i^{\min} \leq \Phi_i^n \leq \Phi_i^{\max} \\ 0 & \Phi_i^n \geq \Phi_i^{\max} \end{cases} \tag{30}$$

It should be noted that the $\Phi_i^{\min}$ and $\Phi_i^{\max}$ are the minimum and maximum values of objective function i in solutions of the Pareto optimal set. Φ_i^n expresses how optimal the n^{th} solution of i^{th} objective function would be. The membership function of n^{th} solution is calculated by equation (31).

$$\Phi^n = \min(\Phi_1^n, ..., \Phi_N^n) \qquad n = 1, ..., N_P \tag{31}$$

The obtained solution including the maximum weakest membership function is selected as the best solution. Equation (32) is used to calculate the implied membership function of this solution (μmax), as follows:

$$\Phi^{\max} = \max(\Phi^1, ..., \Phi^{Np}) \tag{32}$$

Normalized values for objective functions (1) and (2) are expressed by equations (33) and (34), respectively.

$$Cost_{pu} = \Phi_{1,pu} = \frac{Cost - Cost^{\max}}{Cost^{\min} - Cost^{\max}} \tag{33}$$

$$LOLE_{pu} = \Phi_{2,pu} = \frac{LOLE - LOLE^{\max}}{LOLE^{\min} - LOLE^{\max}} \tag{34}$$

4. NUMERICAL SIMULATION

In order to evaluate the effect of DRP implementation on the ESS optimal sizing problem, 2 study cases have been investigated.

A. Input Data

A sample microgrid is used to show the effects of DRP implementation on the proposed model. In the sample microgrid, we have utilized one wind turbine besides four thermal units which characteristics are presented in Table 2. The installed ESS has power investment cost of 40000 \$/MW/year and energy investment cost of 11000 \$/MWh/year [4]. It has been considered that the power can be transferred by a 10 MW line between microgrid and upstream grid. 500 scenarios have been produced to simulate the microgrid load, wind speed and component interruptions. Due to the higher number of scenarios that make the problem extensive and more complicated, a special technique called scenario reduction technique has been used to lessen the existing scenarios to 5 which possibilities are shown in Table 3. Peak load of microgrid is considered to be 17 MW and Figure 2 shows the microgrid load for sample days in spring, summer and autumn in which multiplying peak load by load factors creates sample day's profiles. Fig. 3 shows electricity price in upstream grid. Each scenario has a specific wind speed which is shown in Fig. 4. As expressed in Fig. 5, wind turbine generation can be calculated using scenarios and equation (16). For the upcoming years, microgrid load has been considered constant and therefore the whole plans are considered for one year. The proposed approach was carried on a 2.4-GHz PC utilizing CPLEX 11.0 in GAMS optimization package [37].

Table 2. characteristics of generating units

Unit no.	Bus no.	Cos coefficient (\$/MWh)	Min capacity (MW)	Max capacity (MW)
1	Gas	27.7	1	5
2	Gas	39.1	1	5
3	Gas	39.1	0.8	3
4	Gas	61.3	0.8	3
5	Wind	65.6	0	1
Unit no.	Min. up time(h)	Min. down time(h)	Ramp up (MW/h)	Ramp down (MW/h)
1	3	3	2.5	2.5
2	3	3	2.5	2.5
3	1	1	3	3
4	1	1	3	3
5	-	-	-	-

Table 3. probabilities of reduced scenarios

Scenario	1	2	3	4	5
Probability	0.49	0. 21	0.15	0.09	0.06

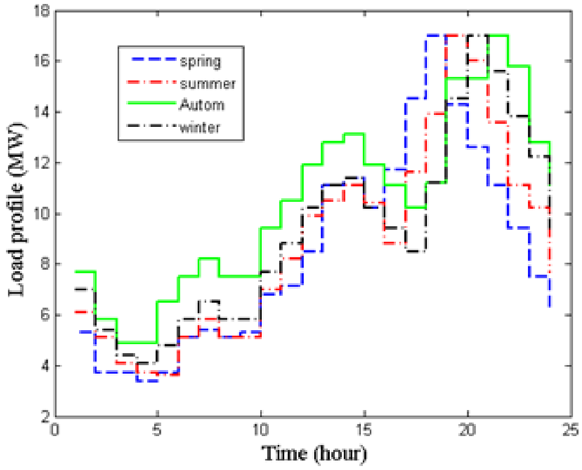

Fig. 2. Load profile for sample days in spring, summer, autumn and winter

B. Results of Simulation in Different Cases

In order to evaluate the effect of DRP implementation on ESS optimal sizing problem, 2 study cases have been investigated and the results are compared:

Case 1: Optimal sizing of ESS without considering DRP
Case 2: Optimal sizing of ESS with considering DRP

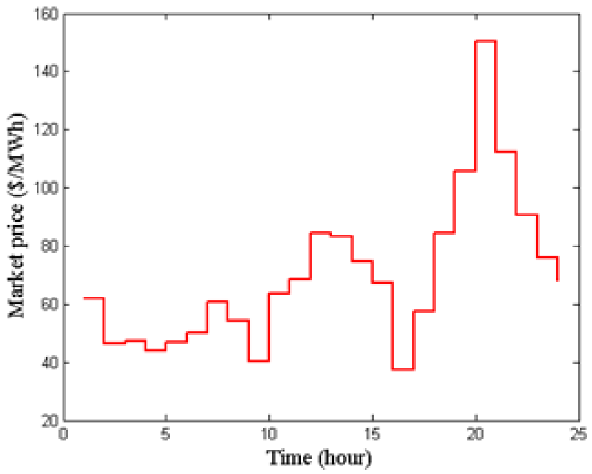

Fig. 3. Forecasted electricity price in upper market

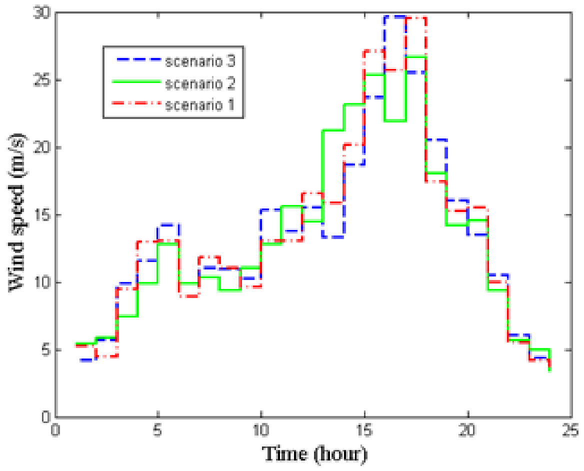

Fig. 4. Wind speed in three scenarios

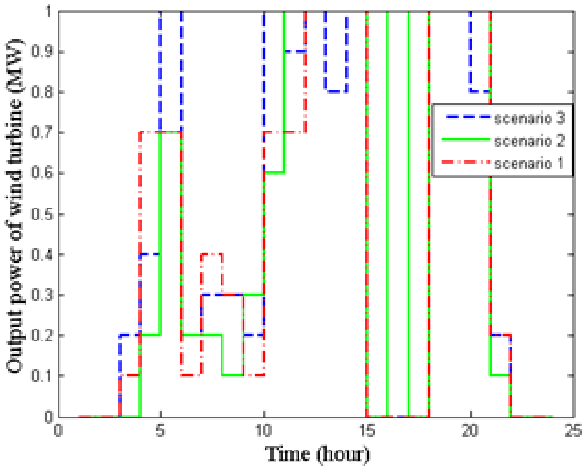

Fig. 5. Output power of wind turbine in three scenarios

Table 4. Pareto optimal solutions for optimal ESS sizing problem without considering DRP (case 1)

#	w1	w2	Total cost ($)	LOLE	$\Phi_1(p.u.)$	$\Phi_2(p.u.)$	$\min(\Phi_1, \Phi_2)$
1	1	0	1930441.582	96	1	0	0
2	0.65	0.35	1934905.822	92	0.977724926	0.041666667	0.041666667
3	0.633333333	0.366666667	1939730.302	88	0.953652375	0.083333333	0.083333333
4	0.616666667	0.383333333	1939730.302	88	0.953652375	0.083333333	0.083333333
5	0.6	0.4	1950555.742	80	0.899637027	0.166666667	0.166666667
6	0.583333333	0.416666667	1961857.702	72	0.843244003	0.25	0.25
7	0.566666667	0.433333333	1967860.942	68	0.813289831	0.291666667	0.291666667
8	0.55	0.45	1974379.462	64	0.780764583	0.333333333	0.333333333
9	0.533333333	0.466666667	1988561.062	56	0.710003112	0.416666667	0.416666667
10	0.516666667	0.483333333	2003631.862	48	0.634804829	0.5	0.5
11	0.483333333	0.516666667	2030057.138	35	0.502951486	0.635416667	0.502951486
12	0.466666667	0.533333333	2048123.858	27	0.412804558	0.71875	0.412804558
13	0.45	0.55	2075752.693	16	0.274945855	0.833333333	0.274945855
14	0.433333333	0.566666667	2086644.253	12	0.220600591	0.875	0.220600591
15	0.416666667	0.583333333	2086644.253	12	0.220600591	0.875	0.220600591
16	0.4	0.6	2086644.253	12	0.220600591	0.875	0.220600591
17	0.383333333	0.616666667	2099332.453	8	0.15729069	0.916666667	0.15729069
18	0.366666667	0.633333333	2112809.533	4	0.09004454	0.958333333	0.09004454
19	0.316666667	0.683333333	2112809.533	4	0.09004454	0.958333333	0.09004454
20	0	1	2130855.733	0	0	1	0

Table 5. Detailed results of case 1

Different parameters	Case 1
ESS rated power (MW)	2.6
ESS rated energy (MWh)	13
Expected unsupplied energy (MWh)	11.50
ESS investment cost ($)	247000
Microgrid generation cost ($)	4563795
Import cost ($)	149319
Benefit from export ($)	2930058
Total cost ($)	2030057

Case 1: Utilizing the weighted sum approach, many solutions are obtained which together create the Pareto front of the proposed model. It should be noted that the effect of DRP has not been considered yet. For more clarification, we have summarized the obtained solutions in Table 4. In order to select the best possible solution among the obtained solutions, min-max fuzzy satisfying technique is utilized. Based on the employed technique, it can be concluded that trade-off solution is Solution #11 in which the maximum weakest membership function is 0.502951486.

Detailed results of obtained solution in case 1 are summarized in Table 5. So, it can be understood from Table 5 that the optimal size of ESS is 2.6 MW at 13 MWh. LOLE is 35 and total cost of microgrid is $ 2,030,057 containing $ 4,563,795 production cost, $ 149,319 power procurement cost, $ 247,000 ESS budget for installation and $ 2,930,058 benefit from power export to the upstream grid. The amount of unsupplied energy is 11.50 MWh.

Case 2: the same procedure of case 1 is repeated for the second case and the results are obtained in the presence of DRP. It can be concluded from the obtained results that the trade-off solution is Solution #9 in which the maximum weakest membership function is 0.5. Detailed results of the obtained solution

Table 6. Pareto optimal solutions for optimal ESS sizing problem with considering DRP (case 2)

#	w1	w2	Total cost ($)	LOLE	$\Phi_1(p.u.)$	$\Phi_2(p.u.)$	$\min(\Phi_1, \Phi_2)$
1	1	0	1596682.011	96	1	0	0
2	0.633333333	0.366666667	1601146.251	92	0.977442935	0.041666667	0.041666667
3	0.616666667	0.383333333	1605970.731	88	0.953065636	0.083333333	0.083333333
4	0.6	0.4	1611258.051	84	0.926349684	0.125	0.125
5	0.583333333	0.416666667	1628098.131	72	0.841259549	0.25	0.25
6	0.566666667	0.433333333	1634101.371	68	0.810926171	0.291666667	0.291666667
7	0.55	0.45	1640619.891	64	0.777989169	0.333333333	0.333333333
8	0.533333333	0.466666667	1647496.371	60	0.743243455	0.375	0.375
9	0.516666667	0.483333333	1669872.291	48	0.630181637	0.5	0.5
10	0.5	0.5	1702203.959	32.165	0.466815071	0.664947917	0.466815071
11	0.483333333	0.516666667	1704332.163	31.165	0.456061612	0.675364583	0.456061612
12	0.466666667	0.533333333	1724992.061	22	0.351670569	0.770833333	0.351670569
13	0.45	0.55	1729941.031	20	0.326664242	0.791666667	0.326664242
14	0.433333333	0.566666667	1743085.184	14.835	0.260249016	0.84546875	0.260249016
15	0.416666667	0.583333333	1751253.854	11.835	0.21897408	0.87671875	0.21897408
16	0.4	0.6	1753369.998	11.121	0.208281553	0.88415625	0.208281553
17	0.383333333	0.616666667	1766058.198	7.121	0.14417018	0.925822917	0.14417018
18	0.366666667	0.633333333	1776542.025	4	0.091197137	0.958333333	0.091197137
19	0.333333333	0.666666667	1776542.025	4	0.091197137	0.958333333	0.091197137
20	0	1	1794588.225	0	0	1	0

Table 7. Detailed results of case 2

Different parameters	Case 2
ESS rated power (MW)	2.2
ESS rated energy (MWh)	11
Expected unsupplied energy (MWh)	15.78
ESS investment cost ($)	209000
Microgrid generation cost ($)	4563796
Import cost ($)	238178
Benefit from export ($)	3341102
Total cost ($)	1669872

in case 2 are summarized in Table 7. So, LOLE is 48 and total cost of microgrid is $ 1,669,872 containing $ 4,563,796 production cost, $ 238,178 power procurement cost, $ 209,000 ESS budget for installation and $ 3,341,102 benefit from power export to the upstream grid. ESS attempts to charge at the times that electricity price is low (off-peak hours) and it attempts to discharge at the times that electricity price is high (peak hours). The amount of unsupplied energy is 15.78 MWh.

It can be understood from the obtained results in Table 7 that by DRP implementation, total cost of microgrid is decreased. By transferring some percent of load from peak time (expensive) periods to another time (cheaper) periods, load profile is flattened and microgrid operating cost is minimized.

C. Comparison results

In order to have a better view and also to see the impact of DRP implementation, obtained results in cases 1 and 2 are summarized in Table 8. In case 2, since the load is shifted from expensive (peak) periods to the cheaper (off-peak) periods, the operating cost of microgrid is less than case 1. So, reduction of operating cost of microgrid leads to the total cost minimization. As shown in Table 8, total cost in case 1 is $ 2,030,057 while this value in case 2 is $ 1,669,872. So it can be concluded that total cost in case 2 has 17.7 % reduction compared to case 1 and this is all because of DRP implementation.

Table 8. Comparison results of case 1 and 2

Different parameters	Case 1	Case 2
ESS rated power (MW)	2.6	2.2
ESS rated energy (MWh)	13	11
Expected unsupplied energy (MWh)	11.50	15.78
ESS investment cost ($)	247000	209000
Microgrid generation cost ($)	4563795	4563796
Import cost ($)	149319	238178
Benefit from export ($)	2930058	3341102
Total cost ($)	2030057	1669872
Total cost reduction (%)	0	17.7

5. CONCLUSION

In this paper, in order to find the best possible size of energy storage system (ESS), a multi-objective optimization model has been proposed. In the proposed multi-objective model, two objective functions are considered as the main goal of proposed work which are namely minimization of total cost and LOLE. Results of both objective functions are in contrast with each other, therefor Pareto solutions should be obtained for both conflicting objective functions. Utilizing the weighted sum approach, many solutions are obtained which together create the Pareto front of the proposed model. Well-known min-max fuzzy satisfying technique is utilized to choose the best possible solution. Also, the effect of DRP on the proposed model is evaluated. Two different cases (with considering DRP and without considering DRP) are investigated and the results are compared to show the effects of DRP implementation. According to the obtained results, the total cost in case 1 is $ 2,030,057 while in case 2 this value is $ 1,669,872. So it can be concluded that the total cost in case 2 has 17.7 % reduction compared to case 1 and this is all because of DRP implementation.

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