Risk-based Battery Energy Storage and Wind Turbine Allocation in Distribution Networks Using Fuzzy Modeling

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The generated power of wind turbines is extremely erratic owing to the intermittence nature of wind speed which can highly affect both the quality and the planning of power systems. Energy storage systems (ESSs) can provide a satisfactory solution for wind power applications by alleviating the harsh fluctuations pertaining to wind production and also providing ancillary services to the power system which in turn causes to increase in the infiltration of wind power in the power systems. Previous studies represent that suitable location and size of ESS units in distribution networks can bring many benets such as peak shaving, loss reduction and reliability improvement. Under this context, this paper proposes a new risk-based method to determine optimal location and capacity of ESS units and wind turbines simultaneously. The proposed method is formulated as multi objective model which includes three objectives: monetary cost, technical risk and economic risk. In addition, the uncertainties considered in this problem include: (i) future load growth of system, (ii) wind generation and (iii) electricity market price. The aforementioned uncertainties are modeled using fuzzy numbers. The proposed optimization problem has been successfully solved using non-dominated sorting genetic algorithm (NSGA-II) and eventually, a "max-min" approach is employed to select the best solution among the obtained Pareto optimal set. The numerical studies performed on the 9-node and 33-node distribution systems indicate the advantages and sufficiency of the proposed methodology. © 2018 Journal of Energy Management and Technology

keywords: *Energy storage system; Wind energy sources; Fuzzy modeling; Risk management.*

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NOMENCLATURE

P_L Minimum possible value of network load

P_M Mean value of network load

P_R Maximum possible value of network load

PW_L Minimum value of the generated power by wind turbine

PW_M Mean value of the generated power by wind turbine

PW_R Maximum value of the generated power by wind turbine

C_{Tmax} Upper bound of electricity market price

V_{min} Minimum limit of voltage

V_{max} Maximum limit of voltage

A_i The area under the membership function of voltage between V_{min} and V_{max}

A_{or} The area under the membership function in the right side of the V_{max}

A_{ol} The area under the membership function in the left side of the V_{min}

P_{max} The allowable maximum limit of the loading constraints

S_{P_k} Risk due to violation of the loading constraints

S_{V_k} Risk due to violation of the voltage constraints

A_r The areas under the membership function in the right side of P_{max}

A_l The areas under the membership function in the left side of P_{max}

S_{VD-MAX} Risk of over/under voltage in nodes

S_{PL-MAX} Risk of overloading in lines

S_{PS-MAX} Risk of overloading in substation

S_{VDk} Possibility degree of over/under voltage occurrence in the kth load node

S_{PSk} Possibility degree of overloading occurrence in the kth substation

S_{PLk} Possibility degree of overloading occurrence in the kth line segment

NL Set of load nodes

NS Set of substations

αN Set of doubles whose elements are indices of nodes connected by line segments

f_T Technical risk objective function

$\tilde{P}_{Si}$ The purchased powers from the main grid through the ith substation as TFN after allocation of the ESS and wind generation units (in MW)

$\tilde{P}_{SOi}$ The purchased powers from the main grid through the ith substation as TFN before allocation of the ESS and wind generation units (in MW)

$\tilde{C}_{EO}$ Costs of the purchased powers by the Disco from the main grid through the ith substation as TFN before allocation of the ESS and wind generation units (in \$/MWh)

$\tilde{C}_E$ Costs of the purchased powers by the Disco from the main grid through the ith substation as TFN after allocation of the ESS and wind generation units (in \$/MWh)

$\tilde{C}_T$ Electricity market price as TFN (\$/MW h)

$\tilde{P}_{wi}$ The generated power by ith wind turbine as TFN (MW)

OC_{Wind} Operation costs of the wind turbine (\$/MWh)

P_{Bi} Charge/discharge power by the ith battery (MW)

MC_B Maintenance cost of battery (\$/MWh)

f_E Economic risk-based objective function

$\tilde{f}_M$ Monetary objective function (\$)

NN Total number of buses in the network

C_{Bi} Battery capacity in the ith location (MW)

C_{wi} Wind turbine capacity in the ith location (MVA)

IC_B Investment cost of battery (\$/MW)

IC_W Investment cost of wind turbine (\$/MVA)

T The horizon planning year (year)

$\Delta \tilde{V}_{ij}$ The voltage drops across the line segment connecting nodes i and j (V)

R_{ij} The line segment resistance of branch between i, j (Ω)

Z_{ij} The line segment impedance of branch between i, j (Ω)

d The discount rate (%)

$\tilde{P}_{loss0}$ The network power losses before battery and wind turbine allocation (MW)

$\tilde{P}_{loss}$ The network power losses after battery and wind turbine allocation (MW)

PF_W Power factor of wind turbine

f_{Mmax} The maximum values obtained by monetary objective function $R(f_m)$

f_{Tmax} The maximum value obtained by technical risk objective function f_T

f_{Emax} The maximum value obtained by economic risk objective function f_E

f_{Mmin} The minimum value obtained by monetary objective function $R(f_m)$

f_{Tmin} The minimum value obtained by technical risk objective function f_T

f_{Emin} The minimum value obtained by economic risk objective function f_E

1. INTRODUCTION

The increasing penetration of distributed energy resources (DER) has resulted in the proliferation of advanced smart grid applications such as energy storage systems (ESSs). With the rapid growth of wind turbines, it will be a big challenge to operate the power system with high wind power penetration securely and reliably due to inherent variability and uncertainty of the wind power [1]. Under this context, the ESS units are considered as an effective tool to enhance the flexibility and controllability, not only of a specific wind farm, but also of the entire grid. Therefore, optimal planning of these resources is a crucial challenge for distribution system operator (DSO). Among renewable energy sources, wind power is one of the most beneficial sources because it can be easily produced by a wind turbine in comparison with other DER units such as micro-turbines. According to the estimation of International Energy Agency (IEA), the annual wind-generated electricity of the world will reach 1282 TW by 2020, nearly 371% increase from 2009. By 2030, that figure will reach 2182 TW almost doubling the year 2020 production [2].

However, extensive penetration of the wind power raises a problem of system instability such as the risks of secure and economical operation of distribution network, due to intermittent nature of wind speed [3]. The wind power variation can also degrade the grid voltage stability due to the surplus or shortage of power [4]. To solve the problem, ESS units can be used in the power system [5]. An ESS has the ability of flexible charging and discharging. Recent development and advances in the ESS and power electronic technologies have made the application of energy storage technologies a viable solution for modern power application. ESS can be installed at any section of a power system. By installing energy storage devices, customers can benefit from their advantages [6]. However, optimum design of the ESS units (location and capacity) is very important challenge to the proper utilization of these resources in distribution networks.

From another perspective, several articles have examined the problem of determining the optimal capacity and size of various battery technologies [6–9]. The optimal location of the batteries is determined in [9] with presence of wind power using particle swarm optimization (PSO) algorithm. In [10], a

method was presented for allocation of ESS in a distribution system with high penetration of wind energy. In [11], optimal operation of distribution networks with wind-based embedded generation and BSSs were considered. In [12], a binary PSO technique was proposed for optimal placement and sizing of the BESS in a distribution system to reduce the distribution power loss. In [13], the distribution systems integrated with both ESS units and renewable energy resources were assessed from the point of adequacy and economic. A hybrid multi-objective PSO approach is proposed in [14] to minimize the power system cost by searching optimal sitting and sizing of storage units under consideration of uncertainties in the wind power production. In [15], an active distribution network is developed by obtaining optimal location, capacity and power rating of the battery units for several objects.

One of the important applications of ESS units in distribution networks is supporting the microgrids (MG) in islanded mode. The ESS and DER planning in MGs are applied in the prior literature by various modellings such as robust optimization [16], scenario-based bi-level model [17] and stochastic multi-objective programming [18]. Research [19] focuses on the optimal allocation of storage systems in active distribution networks by defining a multi-objective optimization problem at finding the optimal trade-off between technical and economic goals. In [20], a new battery operation strategy is proposed for better utilization of energy storage system and mitigation operational risk from price volatility based on a new model. In [21], a mixed-integer second-order cone programing (MISOCP) model is presented to solve the optimal operation problem of radial distribution networks with energy storage. In [22], a proposed approach is presented for placement of distributed generation (DG) units in the distribution networks by defining a multi-objective optimization problem. Some studies have investigated the distribution system planning problem in the presence of ESS units with conflicting objectives using multi-objective approaches [23–25].

In the proposed planning problem, a powerful decision-making tool should be assigned for DSOs in order to model the uncertainties associated with the intermittent power generations of wind turbines, electricity market prices, and the electric load. The motivation of this study is to provide such a tool. In recent years, many approaches have been proposed for modelling the various uncertainties with different assumptions. The literature suggests a wide range of models and methods for modelling the uncertainties of the planning problems such as stochastic programming [18], point estimate methods [26], probabilistic approach [17], Monte Carlo simulation [1], and robust optimization [16].

A common drawback of the above-listed works is that they did not account the technical and economic risks pertaining to uncertainties in the planning stage. Another drawback in the literature is related to the proper treatment of the nonlinearity and nonconvexity of the problem. The above-mentioned papers either use nonconvex formulation of the planning problem or only address the economic aspects without considering the technical constraints of the networks (e.g., network power flows and bus voltage constraints). Also, previous works not referred here have provided valuable contributions to the application of ESS units for mitigating wind uncertainty and they have generally considered uncertainty of the problem by simple assumptions such as Monte Carlo simulation and stochastic programming. However, many of the mentioned papers failed to address distributed renewable energy contribution to reduce technical and financial risks.

To address the aforementioned issues, this paper proposes a new formulation to determine the capacity and location of ESS units and wind energy sources, considering uncertainties in distribution networks. These uncertainties could lead to some risks in determining the optimal siting and sizing for energy storage and wind energy sources in distribution system planning. In this paper, the fuzzy method is used for modelling the different uncertain parameters [24, 30]. A multi objective model is formulated in this paper to incorporate both economic and technical objectives into the optimization process and subsequently NSGA-II is used to minimize the proposed multi-objective function optimization [27]. Finally, max–min decision-making approach is employed to select the best optimal solution among the Pareto-optimal set of solutions obtained using the NSGA-II.

The novel contributions of this paper are six-fold:

- Proposing a multi-objective optimization model to simultaneous ESS and wind turbine planning in distribution networks considering economic and technical issues.

- Constructing the integrated ESS and wind turbine allocation model considering operation and planning objectives based on supply sufficient MINLP from DSO point of view.

- Exploring the conflicting requirements of economic and security criteria for ESS scheduling and proposing a multi-objective framework for highlighting the trade-off between them.

- Considering the financial and technical risks pertaining to the uncertainties of the problem.

- Dealing with uncertainty of the proposed problem through applying a novel fuzzy sets modelling.

- Employing NSGA-II to minimize the problem and applying max–min decision-making approach to select the best optimal solution among the Pareto curve.

This paper is structured as follows. The modelling of the uncertainties in the system using fuzzy numbers will be presented in section 2. The mathematical formulation of the problem will be presented in section 3. The proposed optimization algorithm (i.e. NSGA-II) for solving the problem and also fuzzy decision-making method are explained in section 4 and a case study is given in section 5 to show the performance of the proposed method.

2. UNCERTAINTIES MODELING OF THE PROPOSED PROBLEM

In planning of a distribution system, some system information is subject to uncertainty. For example, generation power of a wind turbine depends on the wind speed and or network load is time-variant. Given the intermittency and uncertainty of renewable energy, a variety of technologies are used to ensure the power supply to customers including ESS units. To consider the negative effects of these uncertainties on the planning problems, an appropriate technique should be utilized. The main problem is that the DSO cannot be sure about the capacity of wind turbines which may be installed in a specific area and its operating schedule. So far, disparate techniques have been used for uncertainty modeling. Probabilistic method is one of the methods for modeling uncertainty. In this paper, it is assumed that we have some statistical data from the past. But if there

is no historical data available, fuzzy technique can be used to uncertainty modeling.

The fuzzy set theory is an effective method to model uncertain parameters that were proposed by Zadeh in order to manage data with non-statistical uncertainty. It allows us to describe partial membership of objects in a set by ill-defined boundaries. Fuzzy set theory can be considered as an extension of n-valued logic if the number of the admissible logic values tends to infinity. Because, the major advantage of this theory is that it can be used to model inexactly information. In many studies, the probability method is used to uncertainty modeling. But, the concept of possibility is used in this paper instead of the concept of probability. The concept of possibility in this theory is shown as numbers between zero and one for modeling of uncertainties [28]. In fact, in this method the uncertain parameter is described using linguistic categories which have fuzzy boundaries. One of the important properties of fuzzy theory is ease of calculation compared with probabilistic methods. The fuzzy set has many advantages in decision-making process (i.e., it can obtain the membership function of output variables and model the real-world conditions and is good for big and complex problems). Thus, according to the above content, theory of fuzzy numbers is suitable for practical applications. Types of membership functions and their shapes can be selected based on computational experience.

In this paper, the uncertain parameters for distribution system includes:

- Future load growing of system

- Wind power generation

- Electricity market price uncertainty modelling

- Voltage and loading constraints modelling.

In what follows the modeling each of these parameters is described.

A. Load Modelling

According to the development of technology and industry, load demand is growing rapidly. Therefore, the predicting of the exact value for the load consumption is not possible. In this paper, fuzzy method is implemented for modelling the uncertainty of the problem. The load modelling is presented as triangular fuzzy number (TFN) P with three points (P_L, P_M, P_R) and is shown in Fig. 1. These three points (P_L, P_M, P_R) are lowest possible value, mean value and maximum possible value of network load, respectively.

B. Wind Power Generation Modelling

Because the stochastic behavior of wind speed, the uncertainty of wind power generation is also modelled as TFN $\tilde{P}_W$ ith three points (PW_L, PW_M, PW_R) that is shown in Fig. 2. The generated power by wind turbines is considered by mean value (PW_M) and deviation (e). The values of PW_L and PW_R are formulated as follows:

$$PW_L = (1 - e) \times PW_M \tag{1}$$
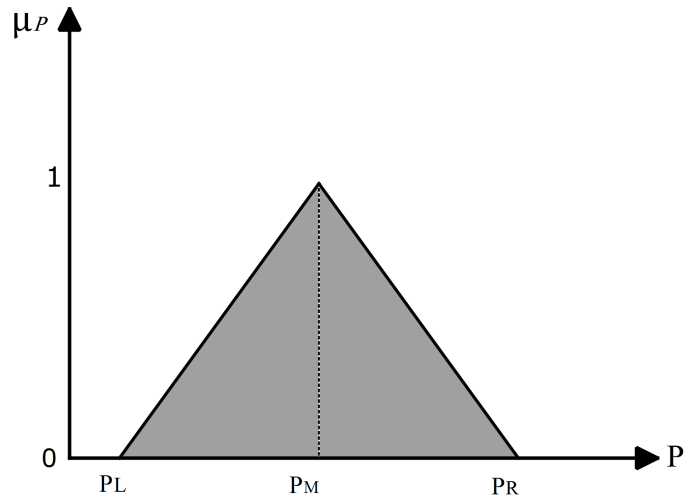
$$PW_R = (1 + e) \times PW_M \tag{2}$$

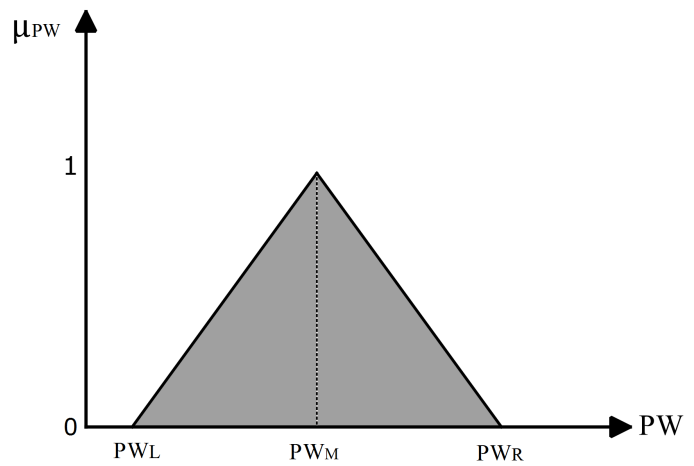**Fig. 1.** Triangular membership function for power load.

Fig. 2. Triangular membership function for the generated power by wind generation unit

C. Electricity Market Price Uncertainty Modelling

According to electricity market conditions, DISCO must purchase power from the pool market, while electricity market prices are not fixed and depends on electricity market conditions. With respect to these conditions, variation of electricity market price is modelled using TFN $(\tilde{C}_T)$. In this work, an upper limit (C_{Tmax}) is considered for the electricity market price. As can be seen in Fig. 3, if electricity market price exceeds the upper limit (C_{Tmax}), DISCO will face with an economic risk.

D. Voltage and Loading Constraints Modelling

The distribution systems are characterized by their prevailing radial nature and high R/X ratio. This renders the load flow problem ill-conditioned. Therefore, conventional methods such as Newton-Raphson or Gauss-Seidel are not suitable for distribution systems. Also, early research indicated that standard load flow methods fail to converge for ill-conditioned test systems and they present that for radial distribution systems the backward/forward sweeping method is more appropriate than other methods especially in the case of presence of DER units in the network [16–18]. Therefore, in this paper the backward/forward sweep load flow algorithm is employed to calculate the power
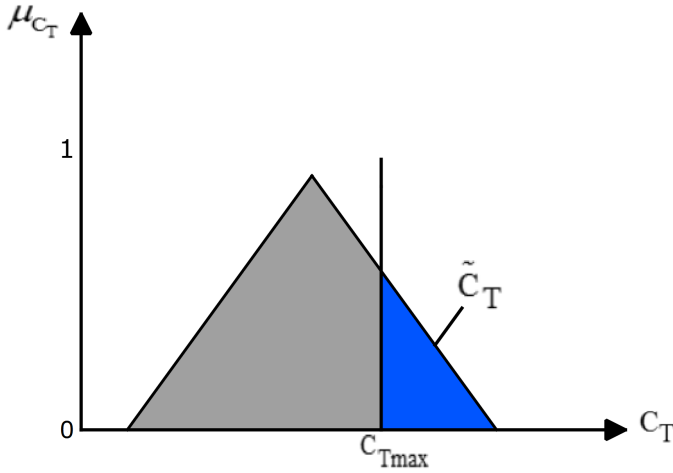
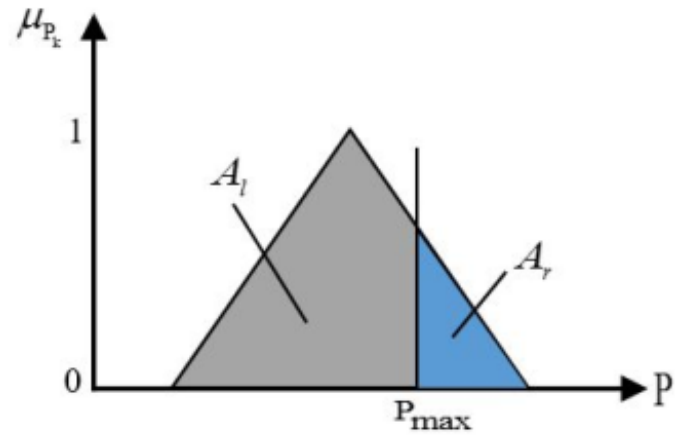**Fig. 3.** Triangular membership function for electricity market price modelling
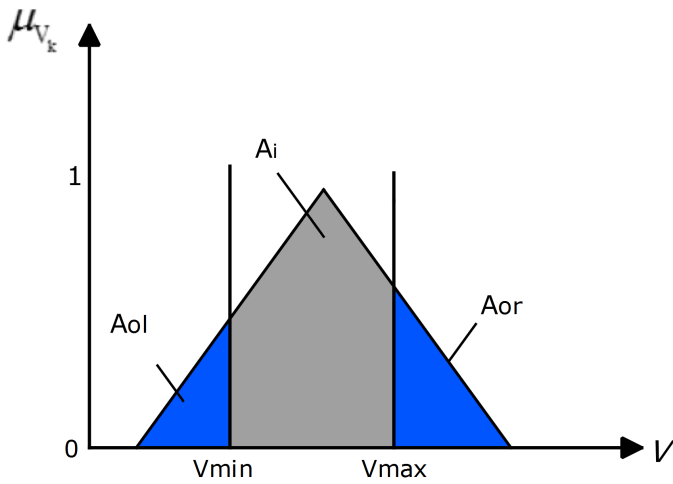

Fig. 4. Voltage constraint in fuzzy domain

losses of system. This load flow is implemented as fuzzy because of the fuzzy modelling of loads. In the other words, the network model will be transferred to fuzzy domain due to fuzzy modelling of parameters. Therefore, results of load flow such as power flow through the lines, voltage of busses as well as loading of substations and line segments will be obtained as TFN.

Modeling of the voltage constraint at node k is described as TFN ($\tilde{V}k$). The voltage constraint at node k should not be less than V_{min} and more than V_{max}. This voltage constraint in fuzzy domain can be defined as below:

$$V_{min} \lesssim \tilde{V}_k \lesssim V_{max} \tag{3}$$

According to Fig. 4, violation of the voltage constraint with a possibility degree is calculated as follows:

$$S_{v_k} = \frac{A_{ol} + A_{or}}{A_i + A_{ol} + A_{or}} \times 100\% \tag{4}$$

By changing the fuzzy voltage in the nodes, the ratio between these areas will change accordingly. Therefore, the possibility degree of violation for the voltage constraint will also change.

As regard to the proposed fuzzy based power flow method, the loading constraint in the line segments and substations is

Fig. 5. Loading constraint in fuzzy domain

also modeled as TFN $\tilde{P}_k$. The loading constraint modeling in fuzzy domain has been graphically shown in Fig. 5. This loading constraint should not exceed P_{max}. Otherwise, the related risk will be increased. This loading constraint is formulated as follows.

$$\tilde{P}_k \lesssim P_{max} \tag{5}$$

Thus, possibility degree due to violation of this loading constraint is calculated as follows:

$$S_{P_k} = \frac{A_r}{A_l + A_r} \times 100\% \tag{6}$$

By increasing the values of S_{P_k} and S_{V_k}, the risk related to violation of loading constraint and violation of voltage constraint will increase, respectively.

3. PROBLEM FORMULATION

In this paper, a multi-objective framework is presented for optimal simultaneous planning of ESS units and wind turbines in distribution network. A solution using NSGA-II algorithm to allocate the ESS units for minimizing wind-penetrated power system operation cost (maximizing wind power penetration) is proposed. The uncertainty of problem is considered as an essential part of the cost probability optimization problem to determine the ESS and wind turbine placements and sizes. The proposed problem is formulated as a constrained mixed integer nonlinear programming (MINLP) with both locations and sizes of storage devices and wind turbines being discrete. The objective function encompasses the wind probability and power system operation cost. The objective function is restricted by equality and inequality constraints. The objectives incorporated into the model include the monetary costs, technical risk and economic risk due to electricity market price uncertainty from the viewpoint of DISCO. Each of these objectives are formulated in this section, individually and eventually have formulated as multi-objective model with some practical constraints.

A. Technical Risk Objective Function

Uncertainty of the parameters could lead to some risks on the distribution system. According toFig 4, the risk due to violation of the voltage constraint in all the network nodes is determined via Eq. (4). Then, among the obtained results, the maximum
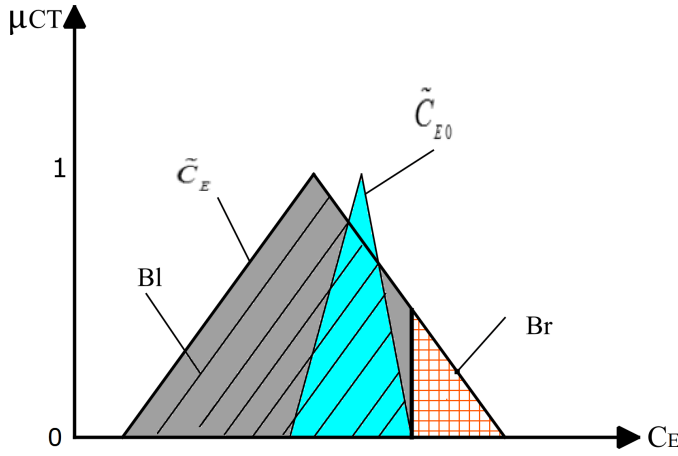
Fig. 6. Graphical representation of $\tilde{C}_{E0}$ and $\tilde{C}_E$

value is being selected as risk of over/under voltage in nodes which can be formulated as the following equation:

$$S_{VD-MAX} = \max\{S_{VDK}|k \in NL\} \qquad (7)$$

Similarly, the risk of overloading in the line segment and substation is defined as the following equation, respectively:

$$S_{PS-MAX} = \max\{S_{PSK}|k \in NS\} \qquad (8)$$

$$S_{PL-MAX} = \max\{S_{PLK}|k \in \alpha N\} \qquad (9)$$

Finally, the technical risk described through considering the following formula.

$$\min f_t = \max\{S_{VD-MAX}, S_{PS-MAX}, S_{PL-MAX}\} \qquad (10)$$

B. Economic Risk Objective Function

Economic risk is calculated by comparison with the cost of the purchased power from the upstream system in two states before and after allocation of energy storage and wind generation units in distribution system.

$$\tilde{C}_{E0} \le \tilde{C}_E \qquad (11)$$

$$\tilde{C}_E = \sum_{i=1}^{N_s} \tilde{P}_{Si} \times \tilde{C}_T + \sum_{i=1}^{NN} \tilde{P}_{Wi} \times OC_{Wind} + \sum_{i=1}^{NN} |P_{Bi}| \times MC_B \quad (12)$$

$$\tilde{C}_{E}0 = \sum_{i=1}^{N_s} \tilde{P}_{Soi} \times C_{Tmax} \qquad (13)$$

The degree of possibility of Eq. (11) and Fig. 6 is defined as:

$$S_{CE} = \frac{B_r}{B_r + B_l} \times 100\% \qquad (14)$$

According to Eq. (

$$\min f_E = S_{CE} \qquad (15)$$

As a result, the larger values of $S_C E$ denotes the greater economic risk for DISCO.

C. Monetary Objective Function

The application of ESS units to shave peak load is similar to demand side management programs that shift demand use of energy from peak to off-peak periods. In this application, energy is stored within ESS during off-peak times and is released when the load is high. Furthermore, the ESS units can properly reduce the fluctuations of wind generation by optimal adjusting its own production. However, the economic feasibility of this usage of energy storage should be justified since ESS units are expensive in installation and maintenance costs. The rst and second part of the monetary objective function consists of investment cost of the battery units and the wind turbines, respectively. The third and fourth parts are operation and maintenance costs of the batteries and wind turbines, respectively. Also, the last part of this function is related to the power loss cost. Finally, the monetary costs can be formulated as follows:

$$\min \tilde{f_M} = \sum_{i=1}^{NN} C_{Bi} \times IC_B + \sum_{i=1}^{NN} C_{wi} \times IC_W +$$
$$8760 \times \sum_{t=1}^{T} \mu^t \sum_{i=1}^{NN} \tilde{P}_{Wi} \times OC_{Wind} + 8760 \times \sum_{t=1}^{T} \mu^t \sum_{i=1}^{NN} |P_{Bi}|$$
$$\times MC_B - 8760 \times \sum_{t=1}^{T} \mu^t (\tilde{P}_{loss0} - \tilde{P}_{loss}) \times \tilde{C}_T \qquad (16)$$

$$\tilde{P}_{loss} = \sum_{(i,j) \in \alpha N} \Delta \tilde{V}_{i,j}^2 \times \frac{R_{i,j}}{Z_{i,j}^2} \qquad (17)$$

$$\mu = \frac{1}{1+d} \qquad (18)$$

Allocating ESS units for this application involves determining the size and the location of ESS units to be installed (i.e. planning decisions) as well as the control strategy of those allocated ESSS units (i.e. operational decisions).

D. Multi-Objective Function Modelling

According to three objective function mentioned in the previous section, the modelling of multi-objective programming with conflicting objectives in order to allocate the ESS units and wind generation units in distribution system can be formulated as follows.

$$\min\{f_T, f_M, f_g\} \qquad (19)$$

S.T

$$\frac{P_{Wi}}{PF_W} \le C_{Wi} \quad i = 1, 2, ..., NN \qquad (20)$$

$$C_{Wi} \le C_{Wmaxi} \qquad (21)$$

$$SOC(t) = SOC_0 + \eta^{CH} P_t^{CH} - P_t^{DIS}/\eta^{DIS} \quad \forall t \qquad (22)$$

Eq. (20) shows the limitation of the generated power by the wind turbine, considering the power factor (PF_W). Therefore, the generated power by the wind turbine must be less than the capacity of wind turbine. Eq. (21), shows the allowable maximum limits due to the capacity of wind turbines. In the other words, installation of wind turbines is not possible in some candidate places because of technical, financial or geographical reasons. Also, the state of charge (SOC) of ESS units can be calculated by Eq. (22). ESS units are used to time-shift electric energy from wind generation. The ESS unit is charged using wind power in excess of the load or distribution capacity that would otherwise be curtailed and discharged during peak load hours of the day when it is most valuable. By changing the site and size of the ESS units and wind turbine, the obtained results for the three objectives function will also change significantly.

4. SOLUTION APPROACH

In this paper, the proposed long-term planning problem has been formulated on the basis of multi-objective MINLP in which the obtained model is non-convex (due to considering load flow computations and some practical constraints) non-smooth and non-linear, which as a result will be a NP-hard problem. Under this context, the exact methods such as CPLEX cannot solve the problem, thereby we used a metaheuristic population-based algorithm to solve the problem in appropriate time. In this paper, NSGA-II is employed to solve the optimization problem in multi-objective functions. NSGA-II has become an efficient tool for solving the nonlinear, nondifferentiable, multi-model as well as discrete variables optimization problems due to its flexible applications and better robustness in controlling parameters [29]. It has already been widely utilized to solve the multi-objective optimization problems on power system by searching for an acceptable Pareto-optimal set. This algorithm tries to minimize all three functions simultaneously.

A. Optimization of the proposed Problem using NSGA-II Algorithm

In placement of ESS and wind generation units, the decision variables are the site and size of battery and wind turbine in each candidate site. Since the binary coding in continuous variables is difficult, the decision variables are encoded by using real numbers in this paper. According to Fig. 7, the suggested chromosome includes two sections. The first section of the chromosomes shows the generated power by wind turbines in the ith location so that its lower limit is set to be zero ($ai = 0$) and also upper limit equal to $bi = PF_w \times C_{wmaxi}$. The second part of the chromosome also shows the charging/discharging power of battery in the ith location with lower limit equal to $ai = -PB_i$ and upper limit equal to $bi=PBi$. Negative value means the battery charge and positive value means the battery discharge in the candidate sites. In this paper, the generated power by wind turbines is considered with the mean value ($_pWM$) and deviation (e) in each of the candidate sites.

In the proposed NSGA-II based algorithm, a ranking selection method is used to emphasize current nondominated solutions and also a niching method is utilized to maintain diversity in the population. Before the selection is performed, the population is first ranked in several steps. At first, the nondominated solutions in the population are identified. These nondominated solutions constitute the first nondominated front and are assigned the same dummy fitness value. The above procedure is repeated to find the second level of nondominated solutions in the population. Once they are identified, a dummy fitness value, which is a little smaller than the worst shared fitness value observed in solutions of the first nondominated set, is assigned. Thereafter, the sharing procedure is performed among the solutions of second nondomination level and shared fitness values are found as before. This process is continued until all population members are assigned a shared fitness value. The population is then reproduced with the shared fitness values. In the first generation, the nondominated solutions of the first front are stored in the Pareto-optimal set. After ranking in the subsequent generations, the Pareto-optimal set is extended with the solutions of the first front. The nondominated solutions of the extended set are extracted to update the Pareto-optimal set. The overall process of proposed optimization algorithm (NSGA-II) to solve the planning problem in order to optimally design of energy storage and wind generation units in distribution system
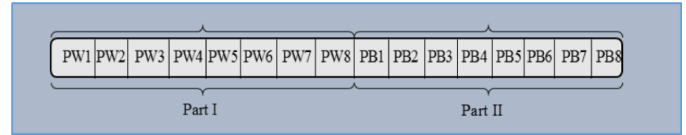

Fig. 7. Coding of the decision variables (chromosomes of NSGA-II).
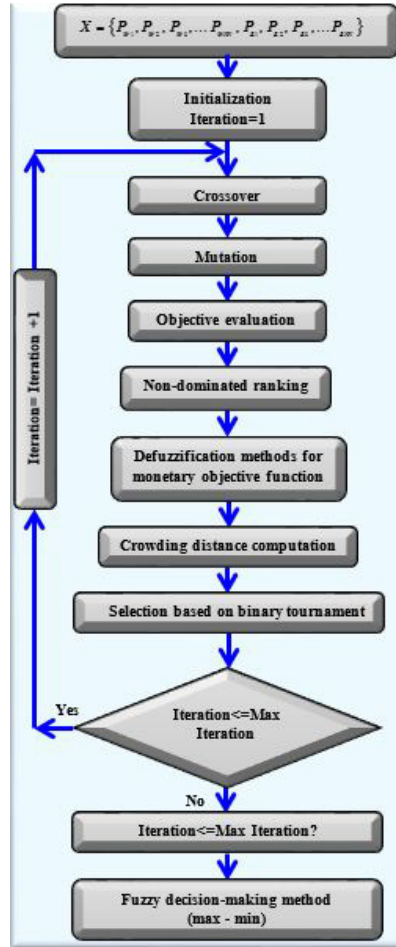

Fig. 8. The overall process of problem-solving for allocation of energy storage and wind generation units

is shown in Fig. 8.

After running the NSGA-II, the pareto-optimal solutions would be reached. However, a method should be utilized for choosing the final solution among these optimal solutions such that it can well represent the preferences of DSO. Many methods have been proposed in this regard [18]. Amongst, the max-min decision-making approach has been introduced as an efficient one due to its simplicity and capability in accounting for DSO's preferences. To this end, fuzzy membership functions are employed for representing the satisfaction degree of decision maker regarding the values of different objectives associated with the optimal solutions [5]. Using of the fuzzy set theory, each of the mentioned objective function can be normalized using a linear membership function as follows:

$$f_{Mnk} = \frac{f_{Mmax} - R(\tilde{f}_{Mk}}{f_{Mmax} - f_{Mmin})} \qquad (23)$$
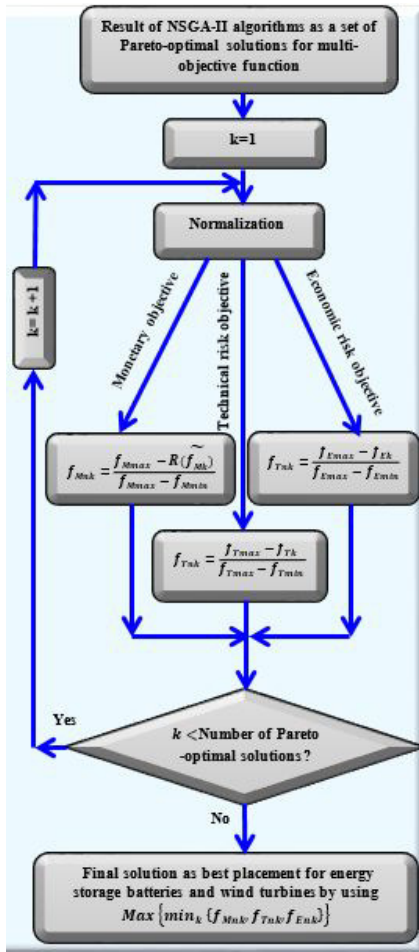
Fig. 9. Max–min computational method

Fig. 10. Distribution network under study

can achieve the goals of smart grids via facilitating the connection of renewable sources such as wind turbines. In this paper, a comprehensive risk-based planning framework is introduced for ascertaining the most cost-effective siting and sizing of ESSs simultaneous with wind turbine allocation so that maximize the profit of distribution network. A possibilistic approach based on fuzzy set theory is further adopted that includes the consideration of the stochastic nature of wind generation, electricity prices and load demand. Such approach allows determining the optimal operation of ESS at each load state. The proposed problem is formulated as multi-objective MINLP model and subsequently has been minimized by NSGA-II.

A. Data and Case studies

In order to demonstrate the effectiveness and performance of the proposed method, two case studies are considered on the 9-node and 33-node distribution systems. The test system as single-line diagram is shown in Fig. 10 [30]. Also, the technical data of 33-node system can be found in [31]. This problem is simulated in MATLAB environment. Technical characteristics related to the distribution networks under study and future load data as TFN and also the costs data are provided in [19,32,33]. All nodes connected to the load are considered as candidate locations for the placement of battery and wind turbine. Capacity of wind turbines in each of the candidate sites is considered as a multiple of 1 MVA (maximum 3 MVA) with power factor 0.9. Also, the maximum capacity of each ESS is considered equal to 2 MWh. Value of this deviation is considered equivalent to 0.1. The charge/discharge power of the battery in each of the candidate sites is considered with the lower limit equivalent to -1 MW and the upper limit equivalent to 1 MW. Some of the parameters of NSGA-II algorithm such as population size, generation, crossover probability, mutation probability equivalent to 300, 50, 0.9, 0.125, respectively.

After the implementation of load flow algorithm, the obtained results by NSGA-II algorithm is shown in Fig. 11. The optimal location and capacity of ESS and wind turbine for both the considered networks are presented in Table 1. A sample of the Pareto-optimal solution obtained using NSGA-II algorithm with the value of the three objective functions and the normalized values are given in Table 2. According to this table, the maximum value in column 'max–min' is selected as the suitable solution in allocation of battery and wind turbine on a distribution system. This best solution obtained using max–min method,

$$f_{Tnk} = \frac{f_{Tmax} - f_{Tk}}{f_{Tmax} - f_{Tmin})} \qquad (24)$$

$$f_{Enk} = \frac{f_{Emax} - f_{Ek}}{f_{Emax} - f_{Emin})} \qquad (25)$$

As a matter of fact, arranging all solutions in Pareto-optimal set in descending order according to their membership function will provide the decision maker with a priority list of nondominated solutions. This will guide the decision maker in view of the current operating conditions. Finally, the obtained solution with the maximum normalized membership value is selected as the most suitable solution.

$$Max\{min_k\{f_M nk, f_T nk, f_E nk\}\} \qquad (26)$$

The basic idea of the Pareto-based fitness assignment is to find a set of solutions in the population that are nondominated by the rest of the population. These solutions are then assigned the highest rank and eliminated from further contention. The overall process of max–min computational method is briefly shown in Fig. 9. The symbol k denotes the number of Pareto-optimal solution obtained using the NSGA-II.

5. NUMERICAL RESULTS

Smart grids have been emerging nowadays as an initiative to operate modern distribution systems in a more economic and efficient way. ESS units are one of the promising technologies that
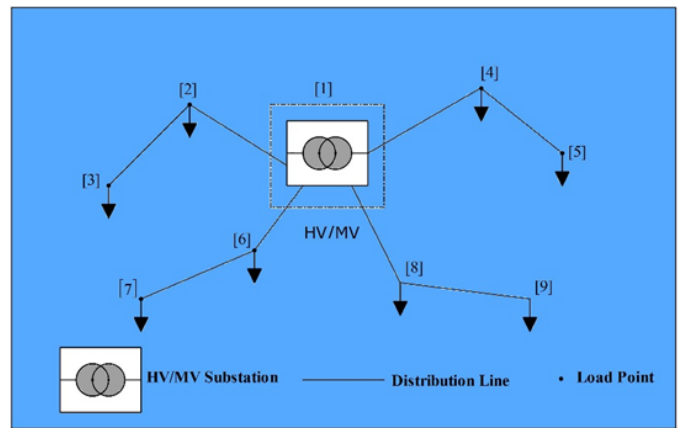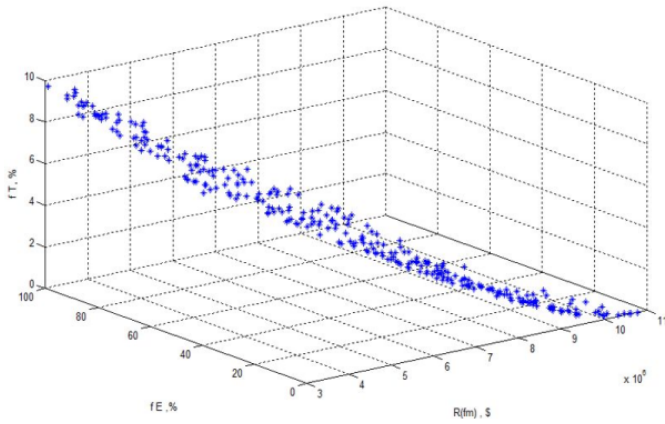
Fig. 11. Pareto-optimal solutions in allocation of wind turbines and batteries on the distribution network

Table 1. Results of optimal ESS and wind turbine planning for both cases.

Study Cases		ESS units	Wind turbines
Case I	location	1, 4, 5, 8	1, 3, 5, 9
(9-node)	Size (MW)	1, 2, 2, 1	2, 3, 2, 2
Case II	location	4, 10, 12, 19, 25, 30	3, 7, 15, 22, 27
(33-node	Size (MW)	350, 500, 500, 450, 400, 300	300, 300, 450, 400, 550

Table 2. Samples of the Pareto-optimal solutions obtained by NSGA-II

K	$f_{MK}(\$)$	$f_{TK}(\%)$	$f_{Ek}(\%)$	fM_{nk}	f_{Tnk}	f_{Enk}	max-min
1	$1.0779*10^7$	0	0	0	1	1	0
2	$0.3066*10^7$	100	9.6967	1	0	0	0
3	$0.3379*10^7$	97.7968	9.2068	0.9594	0.0220	0.0505	0.0220
4	$0.3423*10^7$	95.2816	9.4122	0.9537	0.0472	0.0293	0.0293
10	$0.3491*10^7$	92.3953	9.0501	0.9449	0.0760	0.0667	0.0667
25	$0.8281*10^7$	4.1537	1.4637	0.3239	0.9585	0.8491	0.3239
38	$0.8756*10^7$	19.6769	0.8876	0.2623	0.8032	0.9085	0.2623
42	$0.4750*10^7$	51.1522	7.2021	0.7817	0.4885	0.2573	0.2573
50	$1.0194*10^7$	5.4196	0.0788	0.0759	0.9458	0.9919	0.0759
62	$0.5234*10^7$	49.9208	5.9541	0.7189	0.5008	0.3860	0.3860
75	$0.4198*10^7$	74.9964	7.4108	0.8532	0.2500	0.2357	0.2357
80	$0.7622*10^7$	22.1549	2.3580	0.4093	0.7785	0.7568	0.4093
95	$0.6217*10^7$	50.5039	3.9527	0.5915	0.4950	0.5924	0.4950
102	$0.5150*10^7$	42.1387	6.2711	0.7298	0.5786	0.3533	0.3533
120	$0.6325*10^7$	93.5626	3.4045	0.5774	0.0644	0.6489	0.0644
132	$0.9459*10^7$	4.4958	0.4116	0.1711	0.9550	0.9576	0.1711
138	$0.6128*10^7$	85.6797	4.0888	0.6030	0.1432	0.5783	0.1432
146	$0.7435*10^7$	20.8704	2.4391	0.4335	0.7913	0.7485	0.4335
152	$0.7697*10^7$	3.3939	2.1318	0.3996	0.9661	0.7802	0.3996
187	$0.3606*10^7$	95.4326	8.7063	0.9300	0.0457	0.1021	0.0457
190	$0.7651*10^7$	39.7618	1.8896	0.4056	0.6024	0.8051	0.4056
195	$0.6301*10^7$	17.8173	4.2852	0.5806	0.8218	0.5581	0.5581
196	$0.6198*10^7$	36.9685	4.1173	0.5939	0.6303	0.5754	0.5754
220	$0.9607*10^7$	3.1910	0.2659	0.1520	0.9681	0.9726	0.1520

where k = 196.

In this paper, the best solution has been investigated with two other cases: maximum 6% economic risk and minimum economic risk. With respect to Table 3, the obtained results in each of the three strategies is compared with the base state of system. According to the obtained result by max-min method, risk of overloading in the substation is eliminated. Therefore, we can say that technical risk changed from 100% in the initial condition to 36.9685% after installation of wind energy resources and battery. Also, economic risk which was 15.85% in the initial condition, is reduced to 4.1173% after installation of wind energy resources and battery. However, the monetary cost is equivalent to 6.1984*106 $, under these conditions.

Considering the obtained solution in maximum 6% economic risk, the monetary cost is equivalent to $5.2342 * 10^6$ \$. Thus, monetary cost reductions are observed in this case. But the value of technical risk is increased to 49.9208%. Hence, it can be seen that the monetary cost reduction will be associated with enhance of the economic risk or technical risk in the distribution system. On the other hand, in the case of the minimum economic risk, the monetary cost is increased in comparison with the two previous cases. Value of this monetary cost reached to $1.0779 * 10^7$ \$. But in return, economic and technical risks has been completely removed in the distribution system under study. It is noteworthy that these objectives are in conflict with each other. So that improvement in one of the objectives leads to reduction in other purposes.

In this paper, ESS units are optimally allocated at the distribution system; the charging amount for each ESS should be decided during operation process. The main challenges with wind power integration are power intermittency, ramp rate and limiting wind farm output. The generation-side role of the ESS aims to improve the grid-friendliness of the wind farm to dispatch wind energy such that they can be controlled like conventional power plants. Additionally, it shall be controlled to effectively utilize limited distribution capacity. Fig. 12 introduces the allocation method for both considered case studies. The positive values determine the charging task and also the negative values show the discharging sate of ESS units. When charging/discharging signal is generated, the remained space of ESS for operation is calculated based on SOC level. Due to stochastic characteristic of wind, wind power production is considered as a non-dispatchable resource and sometimes it demonstrates an anti-peak feature, e.g. high wind power during off-peak demand or low wind power during peak demand. The time shifting is to store extra wind energy during periods of low demand and stands ready to dispatch energy to the grid during periods of high demand. Also, the inherently variable nature of wind power can cause fluctuations in frequency and voltage. The ESS can be used to smooth out these fluctuations to keep the system stable. Accordingly, the output power of the ESS needs to be rapidly regulated for absorbing the excess energy during output spikes and releasing energy during output drops. Therefore, the ramping capability is very important for the smoothing function. The output smoothing at the plant level reduces the need for power quality and ancillary services at the system level.

In order to illustrate the applicability and performance of proposed fuzzy based method, a Monte Carlo simulation is performed to estimate the annual arbitrage benefit of ESS units and also technical and economic risks jef system. This simulation takes into account the optimized ESS operation from the fore-

Table 3. Comparison between the solution of the three strategies

| Parameter	Value before battery installation and wind energy unit installation	Value after battery installation and wind energy unit installation		
		(max-min)	(maximum 6% economic risk)	(minimum economic risk)
Power losses as TFN $\tilde{P}_{loss0}$(MW)	(1.2011 1.4829 1.7943)	0.8132 1.0690 (1.3606)	0.8668 1.1274 (1.4234)	0.7371) 1.0054 (0.5120
Substation loading as TFN, $\tilde{P}_s$ (MW A)	(43.69.05 48.5450 53.3995)	(35.4818 40.8377 46.1936)	(36.8737) 42.1590 47.444	29.1485) 34.9039 (40.6599
Risk of overloading in substation (%)	27.64	0	0	0
Risk of overloading in line segment,(%)	100	36.9718	49.92	0
Risk of over/under voltage in load node (%)	100	22.2465	22.51	0
Monetary objective function, f_M ($)	0	$6.1984*10^6$	$5.2342*10^6$	$1.0779*10^7$
Technical risk objective function(%)	100	36.9685	49.9208	0
Economical risk objective function f_E(%)	15.85	4.1173	6	0
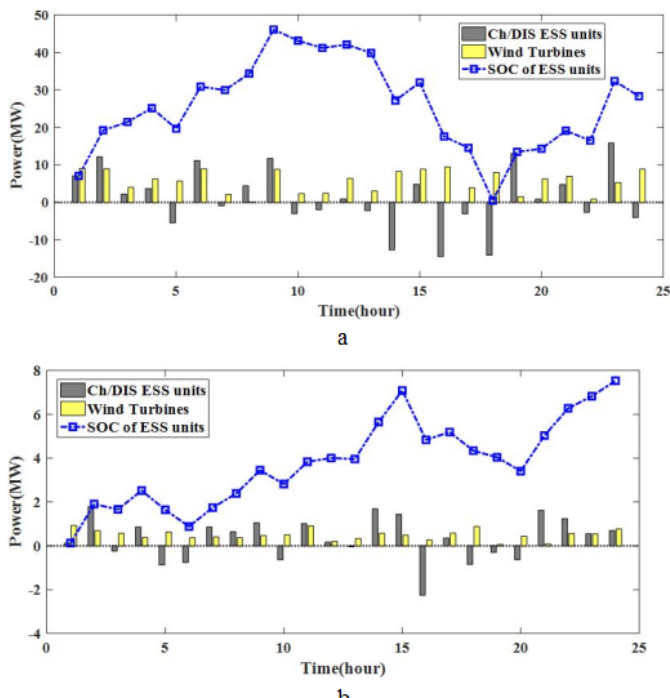
Fig. 12. Operation strategy ESS units and wind turbines through a day (a) 9-node, (b) 33-node.

going stage. It is worth mentioning that the arbitrage benefit obtained from simulation is different from the expected value

determined in the previous step. This difference is attributed to the fact that ESS units might fail to operate as pre-planned if they are fully charged or discharged. The obtained PDF of utilized objectives for planning of ESS and wind turbines are shown in Fig. 13.

According to results presented in Fig. 14, the proposed method can improve the technical specifications of system such as power losses and voltage profile. In the proposed method for optimal planning of ESS units and wind turbines constrains are in appropriate range as can be seen in Fig. 14. In both considered case studies, loss reduction view point provides more benefit to DISCO and as it can be seen from this figure, there is improvement in voltage profile and reduction on power losses in the feeders.

Furthermore, the proposed optimization problem is performed with two different optimization algorithms including MOPSO and SPEAII in order to show the performance of proposed algorithm compared to other conventional algorithms. The optimization results are provided in Fig. 15. The proposed fuzzy-NSGAII algorithm outperforms other algorithms in solving mixed integer nonlinear optimization problem. As an example, the graphical representation of NSGA-II convergence presented in Fig. 15 shows the superior performance of NSGA-II in terms of the number of iterations before stopping compared to other algorithms. Moreover, it is worth mentioning that NSGA-II, as one of the heuristic algorithms, does not guarantee the same solution even after running the same problem several times. Therefore, the NSGA-II run was repeated ten times with different initial populations that were randomly generated. The maximum difference between the optimal solutions obtained was then recorded and found to be less than 5%. Such statistical
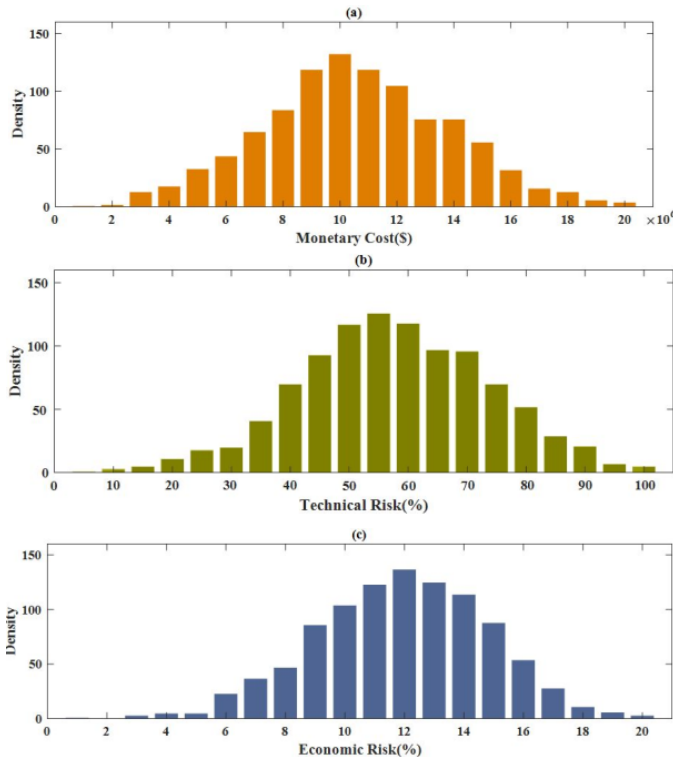
Fig. 13. Monte Carlo simulation results for three considered objectives.
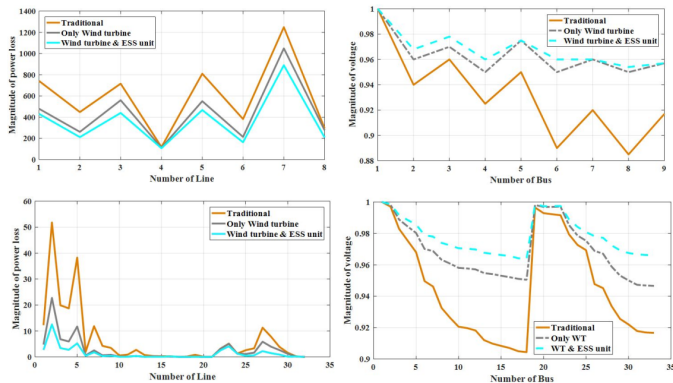

Fig. 14. Power losses and voltage profiles for both case studies (a) 9-node, (b) 33-node.

results also prove the effectiveness of the proposed NSGA-II.

Regarding the results obtained from the considered numerical case studies, the following conclusions are in order:

- The risk analysis performed for different levels of wind power output uncertainty shows a strong improvement on the technical and pecuniary indicators if fuzzy set theory-based uncertainty modelling method is used.

- As it was expected, the increase of the probabilities of uncertain events, i.e., wind power production, load consumption and increase of electricity price during peak-hours, shows the advantage of fuzzy set theory based on the proposed long-term planning in comparison with an optimization based on the expected values.
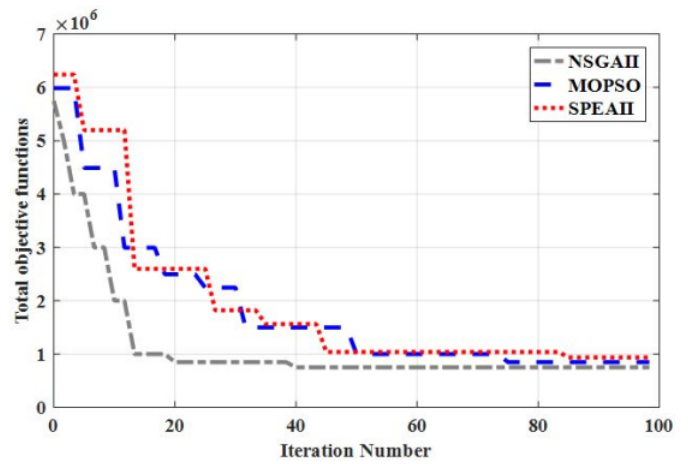

Fig. 15. Optimization process of different optimization algorithms.

- The price variations play a significant role in the system's performance. In particular, with an increase of either the price for the negative imbalance or the peak-hours price, the proposed fuzzy method shows a clear advantage in comparison with the optimization based on the expected values. Thus, there is a threshold probability of uncertain events occurrence above which TFN based on proposed risk indices performs better, which strongly depends on the price variations.

6. CONCLUSIONS

This paper proposes a practical model and efficient method for optimal planning of ESS units and wind turbines. The optimal allocation and control strategy of ESS can help DISCOs to mitigate the risk of the wind generation. Based on the obtained results, the impacts of the optimal allocation of ESS and wind energy resources in reducing the technical and economic risks can be seen clearly. According to these results, it can be seen that the technical and economic risks reduction is directly related to the increase in the financial costs. These obtained results show that the placement of the ESS units and wind turbines is a powerful decision-making tool for risk management in distribution networks. Since the three objective functions conflict with each other, planners should have a priority list to select the best strategy among a series of strategies based on their experience or the requisites of the distribution networks for determining an optimal solution among the Pareto-optimal solutions. From the case study results, the DISCO saves the energy purchasing cost through optimal planning and schedule a more suitable energy purchasing plan. Meanwhile, the ESS optimal allocation method is proved to be effective. Along with development of battery technology and introduction of more stimulus policies, the costs of battery will decrease, which makes the ESS application more feasible in future distribution networks.

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