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Fuzzy Risk-Based Optimal Reactive Power Dispatch in a Wind-Integrated Power System

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Abstract
In this paper, a novel risk-based, two-objective (technical and economical) optimal reactive power dispatch method in a wind-integrated power system is proposed which is more consistent with operational criteria. The technical objective includes the minimization of the new voltage instability risk index. The economical objective includes cost minimization of reactive power generation and active power loss. The proposed voltage instability risk employs a hybrid possibilistic (Delphi-Fuzzy)-probabilistic approach that takes into consideration the operator's experience, the wind speed and demand forecast uncertainties when quantifying the risk index. The decision variables are the reactive power resources of the system. To solve the problem, the modified multi-objective particle swarm optimization algorithm with sine and cosine acceleration coefficients is utilized. The method is implemented on the modified IEEE 30-bus system. The proposed method is compared with those in the previously published literature, and the results confirm that the proposed risk index is better at estimating the voltage instability risk of the system, especially in cases with severe impact and low probability. In addition, according to the simulation results compared to typical security-based planning, the proposed risk-based planning may increase the security and economy of the system due to better utilization of system resources.

Keywords
Optimal reactive power dispatch, Risk quantification, Power system uncertainty, Multi-objective optimization.

1. Introduction

Optimal Reactive Power Dispatch (ORPD), which is implemented to increase the system security and economy, is a special kind of optimal power flow (OPF) problem which relates to reactive power [1]. The goal of this problem is to find the optimal value of reactive power resources in the system to minimize or maximize the objective functions. If the power system component outages are simulated in the optimization procedure, it will be called a Security Constraint ORPD (SC-ORPD) problem [2].

For solving an SC-ORPD, deterministic approaches have been used by Independent System Operators (ISO) for several years because of their high reliability and undeniable simplicity. However, the SC-ORPD has some drawbacks such as the following: deterministic solutions are often over-conservative and non- economic [1]. In addition, it is hard to distinguish between near-violations and no near-violations, a single or slight violation and many severe violation conditions in power system operation [3].

In order to overcome these weaknesses, a risk-based optimization planning is introduced. In this field, the operators must quantify a risk index by composing the probability and the severity of the events [1]. Yet, employing RB-ORPD demands the introduction of a Risk Index (RI) that can well quantify the threats and be understandable by the operators. The common approach for risk quantification is the product of severity and probability of the events. However, due to the very low probability of the events which is calculated from the historical data of the component, this method may lead to the underestimation of the risk. As a result, the operators may take inappropriate preventive or corrective actions. Therefore, it is necessary to employ a method that is capable of estimating the risk of events or uncertainties and the estimated value very well, and is understood and interpreted by the operators.

In Addition, renewable resources like the installation of wind generators are increasing in power systems due to some environmental issues. Some such resources, like doubly-fed induction wind generators (DFIGs), can provide reactive support for power systems. However, they are uncertain reactive providers because of their intermittent nature. Another uncertain parameter that affects power system planning is demand uncertainty that is due to load forecast error. Therefore, to guaranty the security of the system, their uncertainty must be considered in power system planning and operation.

1.2. Literature Review

In [4], a risk-based OPF process is implied for minimizing the influence of social effects. The weather and equipment conditions are considered in the problem formulation. In [5], a new perspective on coordinating system "N-1" criteria and risk for real-time operations is presented.

In [6], a model for calculating risk of outages accounting for remedial measures and the impact of cascading events is presented. Ref. [7] proposes a new stochastic preventive voltage control model for power systems operation. The uncertainty of wind power generation has been taken into account in this reference. In [8], a risk-based multiple-objective (RB-MO) model, simultaneously considering the security and economic objectives, is presented.

In [9], an optimal reactive dispatch scheme under load uncertainty, using the Robbins-Monro method along with the Kiefer–Wolfowitz procedure with random direction, is presented. Probabilistic optimal power flow considering wind uncertainty is presented in [10]. The objective of the presented method is the minimization of expected generation cost and the downside risk. In [11], a weighted chance constraints framework based on an optimal power flow is presented. Multi-objective optimal reactive power dispatch considering wind uncertainties is addressed in [12]. In [13], the authors propose a stochastic optimal power flow that co-optimizes the risk limits and the generation dispatch and achieves an optimal balance between risk reduction and the cost of operation.

Ref. [14] suggests a multi-objective function approach along with the cuckoo search optimization method to address the nonlinear OPF problem in distribution networks. A multi-area decentralized reactive power optimization problem considering the practical constraint of power system devices is studied in [15]. Stochastic multi-objective optimal energy and reactive power dispatch considering the operational cost, load margin improvement and coordinated reactive power reserve management is presented in [16]. The study in [17] represents a method for optimal switching capacitors of the network by using local data including the voltage magnitude to minimize the loss of the system. In [18], a new dispatch approach for multi-area power systems is proposed in which the active power and the reactive power are simultaneously optimized in a decentralized manner with the aid of reactive power support from conventional generators and wind farms. In [19], the optimal reactive power dispatch (ORPD) problem for real power loss minimization, voltage deviation minimization, and voltage stability enhancement is proposed.

In [20], a review of meta-heuristic methods for the solution of the ORPD problem is presented. In this paper, a new meta-heuristic Sine-Cosine algorithm is also proposed to solve the problem. In [21], a risk-based distributionally robust real-time dispatch approach is proposed to strike a balance between the operational costs and the risk. It also considers the nodal voltage security even when the distribution of uncertainties cannot be estimated precisely. Ref. [22] proposes a new simple and easy implementation of Rao-3 optimization algorithm to solve the constrained ORPD problem. Moreover, solar energy, wind energy and demand forecast uncertainties are exploited. The study in [23] presents a method for an active distribution network that considers all energy transactions as well as the reactive power. The simulation is done in a 24-hour time frame to minimize the energy cost.

1.3. Contribution

Based on the literature review, some existing gaps are identified as follows:

1- All uncertain variables are not considered in the reviewed references.
2- The risk is quantified in the literature by the product of the severity and probability of an event. However, because the probability of the events has a very low value in most of the cases in real power systems, the product method may lead to the under-estimation of risk value.
3- Risk is a qualitative concept but must be quantified to be understandable to the operator. Therefore, risks must be quantified consistent with the operator's experience about the events.

To address the aforementioned issues, a novel risk-based ORPD and risk quantification method is presented in this paper.

The contributions of the paper are as follows:

1- To address Issue 1, all uncertain variables including unscheduled events, renewable power generation, and load forecast uncertainty are included.
2- To cover Issues 2 and 3, a hybrid probabilistic-possibilistic voltage instability risk index is presented in this paper. It combines the operator's experiences with the probability and consequence of events using scenario generation as the probabilistic method and the Delphy-Fuzzy as the possibilistic method.
3- Also, for more compatibility with practical issues, conventional and renewable (DFIG wind generator) reactive generation limits are included in the problem formulation.

In addition, the modified Multi-Objective PSO (MOPSO) algorithm with sine cosine acceleration coefficients is utilized to find non-dominated solutions (Pareto-front).

The paper is organized as follows: Section 2 is dedicated to uncertainty modelling. The events, wind, and demand uncertainty are described in this section. Also, scenario generation using the point estimating method is presented in this section. Section 3 presents the proposed method. The multi-objective risk-based optimal reactive power dispatch formulation, the objective functions, and the constraints are described in this section. Section 4 is dedicated to simulation results. Finally, the conclusion is presented in Section 5.

2. Uncertainty modelling

Random outages, intermittent resources (like wind generators which are increasing), and loads (that are always uncertain) are the main stochastic sources of the system. To prevent system security and economy issues, these uncertainties must be considered in planning and operating the systems.

2.1. Modelling Outage of Power System Components

Each power system component can be modelled with a two-state model, as illustrated in Fig. 1. At any time, a component can be either in-service (available) or out-of-service (unavailable). Using this model, the unavailability of each component can be calculated. Mathematically, the long-term average unavailability of any power system component can be calculated by [2]:

$$U=\frac{\lambda}{\mu+\lambda} \tag{1}$$

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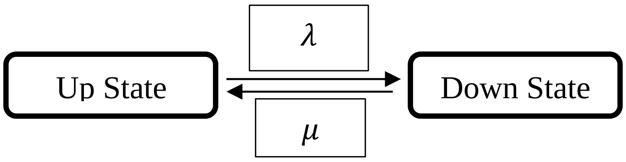

Fig. 1. State space diagram of a repairable component

The probability of finding the component on service is called availability and can be calculated as:

$$A=1-U \tag{2}$$

Unavailability or Forced Outage Rate (FOR) can be used to easily estimate the component outage probability.

2.2. Wind Speed Uncertainty Modelling

The power generation of wind turbines is highly dependent on the wind, which is oscillating. The most common method for modelling wind uncertainty is to use Weibull or Rayleigh Probability Density Function (PDFs) [24]. In this paper, Weibull PDF is used and is given by:

$$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left(-\frac{v}{c}\right)^{k} \tag{3}$$

where c and k can be estimated using historical data of wind speed in any region. The relationship between turbine output power and wind speed can be expressed simply by the linear characteristic curve as follows:

$$P_{wind}=\begin{cases} 0 & 0\leq v<v_{cut\text{-}in} \\ P_{rate}\frac{v-v_{cut\text{-}in}}{v_{rate}-v_{cut\text{-}in}} & v_{in}\leq v<v_{r} \\ P_{rate} & v_{rate}\leq v\leq v_{cut\text{-}out} \\ 0 & v>v_{out} \end{cases} \tag{4}$$

2.3. Demand Forecast Uncertainty Modelling

Demand uncertainty is due to load forecast error and can be modelled using the normal probability distribution function (PDF) [2]. It is assumed that the mean and standard deviation of the total load PDF (μ_D and σ_D) are known. The mean of load distribution is considered to be equal to the forecasted load with a 3% standard deviation in this paper.

2.4. Point Estimating Method

To generate scenarios from PDF of uncertain variables and calculate the expected value of objective functions, Point Estimation Method (PEM) is employed is in this paper. This method requires less computation time compared to the MCS method. PEM is an approximate method in which the information provided by the moments of each random variable K is used for calculating the representatives of the input probabilistic distribution function[16]. By employing the representatives, the statistical characteristics of output variables Z will be calculated (the expected value of Z). These statistical characteristics are a function of M input variables. Using statistical moment, K points and weighting factors are calculated for each random variable as the representative of the PDF. So, totally K× M points and weighting factors must be calculated. Accordingly, the moments characteristic of Z can be calculated by K× M deterministic computation. K can be either 2 or 3 or more but K=3, which is called the 2× M+ 1 scheme, is preferred because of its accuracy and time optimality. The procedure, formulation and steps in this approach are available in [16]. In this paper, two uncertain variables (wind speed and system demand) are considered which lead to totally 5 points (scenarios) for simulation. This method requires less computation time compared to the MCS method.

3. Proposed Method

In this section, the proposed method and the formulations are presented.

3.1. Formulation of Multi-Objective Security Constraint Optimal Reactive Power Dispatch Problem

The general form for multi-objective ORPD is as given in (5). F1 and F2 are the objectives and the other two terms are equality and inequality constraints.

$$\min\begin{cases} F1(x,u) \\ F2(x,u) \end{cases}$$
$$\text{s.t}$$
$$A(x,u)=b,$$
$$X(x,u)>0, \tag{5}$$

The x and u vectors can be expressed as follows:

$$x=[P_{slack}, Q_{slack}, V_L, Q_g] \tag{6}$$

$$u=[V_g, Q_c, T_p, P_w, Q_w] \tag{7}$$

3.2. Fuzzy Voltage Instability Risk Index (F1)

Due to employing long term average unavailability of the component as the probability of component outage, the value of outages probability is mostly near zero. Using a product of probability and consequence of outages, which is a common approach to quantify the system risk, may not reflect the real system risk for a practical purpose. In addition, the risk is a qualitative quantity that must be quantified to be understood better by the operators. Therefore, the operators experience about power system operations and past events must be included in quantifying risks in systems.

To do so, a hybrid probabilistic-possibilistic voltage instability risk index using the Delphi-Fuzzy is introduced in this paper. The proposed index mixes the operator experience about the event's risk, the consequence and probability of outage occurrence, and the uncertainty of demand and renewable energy resources.

To calculate the impact of the events on the Voltage Instability Margin (VIM), L-Index is employed. Using this index, the distance towards voltage instability can be estimated [26]. The expected value of L-index can be expressed using the product of the probability of each scenario (5 scenarios that have been calculated employing PEM) and the calculated L-Index of PQ buses as follows:

$$EL=\sum_{i=1}^{5}\omega_i L_{index,i} \tag{8}$$

The EL is calculated after the simulation of each component outage and will be considered as the consequence of the events. The fuzzy inference system is used for the combination of the consequence and the probability of the outages and then quantification of the voltage instability risk for each PQ bus is performed. The maximum value of the risks calculated for all events is considered to be F1. The advantage of using this method is that the effect of insignificant probability of the events in risk quantification will be ineffective. In addition, by using the Delphi-Fuzzy, the attitude of the operators about the events and their imposed risk will be reflected in the risk quantification process. The Delphi-Fuzzy is an advanced version of the Delphi Method in that it utilizes triangulation statistics to determine the distance between

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the levels of consensus in the expert panel. The method is as follows:

1- Qualified experts are asked to present their views and opinions separately and without any interaction with each other about the subject.
2- A statistical analysis is made on this subjective data.
3- This statistical information is then passed on to selected experts to review the results and present a new estimate.
4- The new estimate will be statistically re-analysed.
5- New information is sent to experts and the re-estimation process continues until an acceptable and stable answer is reached.

Using questionnaires, 10 Iranian power system operators working in Iran Grid Management Company (IGMC) were asked to present their views about the risk limits and rules. The system risk assumed to be a value between 0 and 1. The expected value of L-index ranges between 0-1 and the probability of component outage is between 0-0.3 percent. The answered questionnaires are available in Appendix-I. The operators must define the limits of triangles of low, medium and high level of the probability and impact of the events and risk and fuzzy rules. Figs. 2-4 show the fuzzy variables obtained from the Delphi-Fuzzy procedure. The fuzzy rules are available in Table I. The Min-max and centroid methods are used for fuzzy inference and defuzzification system.

3.3. Operational Cost (F2)

The operational cost includes active power loss and reactive power generation cost as the economic objective of the proposed formulation. The cost of active power loss can be calculated using the following formula [27]:

$$F_{21}=LC=P^* \sum_{k=1}^{N_{T\text{-}Line}} g_k[(V_i^2+V_j^2-2V_iV_j\cos(\delta_i-\delta_j)] \quad (9)$$

where P is considered equal to the average cost of active power in \$/MW and can be calculated using Economic-Dispatch (EDC). P is also used to calculate the capability curve and reactive limits of generators. The reactive power cost can be expressed using a quadratic cost function as follows [28]:

$$F_{22}=C_q=\sum_{i=1}^{N_g} a_{gi}^q Q_{gi}^2+b_g^q Q_{gi}+c_{gi}^q \quad (10)$$

where a_g^q, b_g^q, and c_g^q are estimated using the generator's capability curve. Therefore, the expected value of operational cost (EVOC) can be calculated as follows:

$$F_2=EVOC=\sum_{i=1}^{5} W_i(F_{21}+F_{22}) \quad (11)$$

The economic objectives are calculated in the base case because it is the main operating condition of the system. In fact, following any contingency, system operators must return the network condition to the base case as soon as possible. However, contingencies may lead to voltage instability or violation and cascading outage of the components as a result. Therefore, the technical objective is calculated after the simulation of the outage events.

3.4. Equality and Inequality Constraints

Load flow equations are equality constraints of an OPF problem:

$$P_{G_i}-P_{D_i}-V_i\sum_{j=1}^{Nb} V_j\left[G_{ij}\cos(\delta_i-\delta_j)+B_{ij}\sin(\delta_i-\delta_j)\right]=0 \quad (12)$$

$$Q_{G_i}-Q_{D_i}-V_i\sum_{j=1}^{Nb} V_j\left[G_{ij}\sin(\delta_i-\delta_j)+B_{ij}\cos(\delta_i-\delta_j)\right]=0 \quad (13)$$

Inequality constraints can be divided to non-risk-based and risk-based. A non-risk-based constraint is the one which is considered in the base-case and the risk-based constraints are the power system components and operation limits following an outage. They can be expressed as follows:

3.4.1 Generator Constraints

Generator voltages including DFIGs and load buses have to be restricted by their lower and upper bound in base-case and post-contingency situations:

$$V_{Gi}^{min}\leq V_{Gi}\leq V_{Gi}^{max} \quad (14)$$

$$V_{Li}^{min}\leq V_{Li}\leq V_{Li}^{max} \quad (15)$$

If it is expected that generators operate in the voltage control mode, their generated/absorbed reactive power must be within their limits. The operating point of the generators, the internal voltage, the armature current, and the reactance of the generators are factors influencing this limit. The detailed formulations of the maximum reactive power output of generators according to the field current limit are available in [29]. The maximum reactive power output of each generator is limited by the minimum of filed and armature limits as follows:

$$Q_g^{max}=\min(Q_g^{max\text{-}Field},Q_g^{armature}) \quad (16)$$

Also, the DFIG can control its active and reactive power output independently by using power electronic controllers. With appropriate planning, this ability can improve the power system security. Typically, the stator

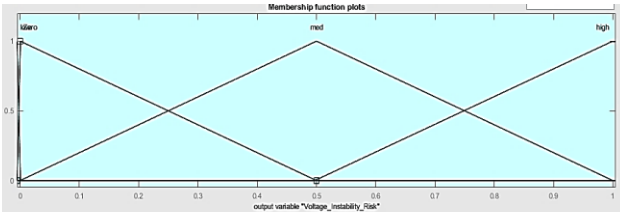

Fig. 2. Fuzzy Output Variable, voltage instability risk

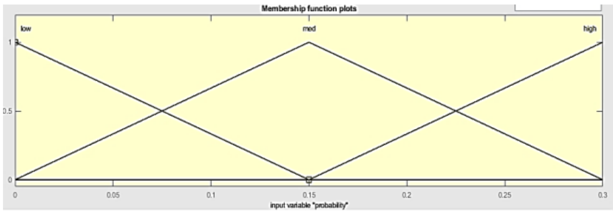

Fig. 3. Fuzzy Input Variable, probability of outages

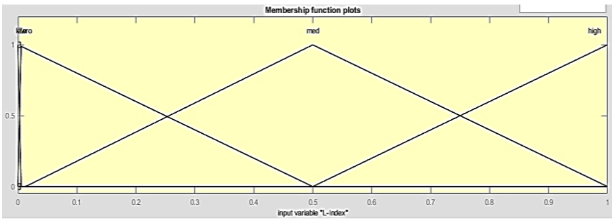

Fig. 4. Fuzzy Input Variable, L-Index

Table I. Fuzzy rules

Risk-Index	Outage Probability			
L-Index		Low	Medium	High
	zero	zero	zero	zero
	Low	Low	Low	Medium

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	Medium	Low	Medium	Medium
	High	Medium	High	High

current is the limiting factor for the DFIG reactive power absorption [29]:

$$Q_w^{max\text{-}stature}=-\sqrt{\left(|V_w|I_w^{max\text{-}stator}\right)^2-\left(\frac{P_w}{1-S_w}\right)^2} \tag{17}$$

The maximum rotor current is the upper limit of reactive power injection:

$$Q_w^{max\text{-}rotor}=-\frac{|V_{w,s}|^2(X_w^s+X_w^m)}{|Z_w^s+Z_w^m|^2}+\frac{|V_w||Z_w^s|I_w^{max\text{-}rotor}\sin\gamma_w}{|Z_w^s+Z_w^m|} \tag{18}$$

$$\gamma_w=\cos^{-1}\left(\frac{P_w|Z_w^s+Z_w^m|^2+|V_{w,s}|^2(R_w^s+R_w^m)}{(1-S_w)|V_w||Z_w^m||Z_w^s+Z_w^m|I_w^{max\text{-}rotor}}\right) \tag{19}$$

So, the reactive power output of the DFIG is limited between these two calculated values:

$$Q_w^{max\text{-}stature}\leq Q_w\leq Q_w^{max\text{-}rotor} \tag{20}$$

3.4.2 Transformer Constraints

The maximum and minimum tap numbers of transformers define this limit as follows:

$$T_i^{min}\leq T_i\leq T_i^{max} \tag{21}$$

3.4.3 Shunt VAR Compensators Constraints

The shunt VAR compensators are restricted by their lower and upper reactive generation bounds:

$$Q_{ci}^{min}\leq Q_{ci}\leq Q_{ci}^{max} \tag{22}$$

3.4.4 Security Constraints

The transmission line loadings and the VSI limit in the base-case and their appropriate risk after contingencies define the security constraints of the proposed formulation. So, they can be defined by:

$$S_{li}\leq S_{li}^{max} \tag{23}$$

$$VSI_i<1 \tag{24}$$

(24) guaranties power system stability in the base-case. Post-contingency security risks are as follows:

$$V\text{-}RISK_j\leq V\text{-}RL \tag{25}$$

$$S\text{-}RISK_j\leq S\text{-}RL \tag{26}$$

$$VSI\text{-}RISK_j\leq VSI\text{-}RL \tag{27}$$

where RL is the system risk limit tolerated by system operators and can be set by the operator’s experience.

3.5. MOPSO with sine cosine acceleration coefficients optimization algorithm

Particle swarm optimization (PSO) is a computational method that optimizes a problem iteratively [30]. The particles fly in the swarm to search for their best solution based on the experience of their own and that of the other particles of the same swarm. PSO has also been applied to multi-objective problems in which the comparison of objective function takes pareto dominance into account when moving the PSO particles, and the non-dominated solutions are stored so as to approximate the pareto front. In MOPSO, velocity and position update equations remain the same as in PSO. Instead, MOSPO uses an extra repository to store the non-dominated solutions.

However, PSO may undergo premature convergences in some cases and be trapped in local optima. Generally, it is desirable that the swarms fly through the search space such that in the early stages the new positions emphasize more on the Pbest and in the Final stages Gbest become more important. It is proved in [30] that the sine and cosine acceleration coefficients will improve exploration and exploitation of the algorithm to overcome the shortcomings. Therefore, in this paper, based on the modified algorithm presented in [30], MOPSO with the sine cosine acceleration coefficients is introduced and employed to find the Pareto front. The sine and cosine acceleration coefficients are:

$$c_1=\sigma*\sin\left(\left(1-\frac{M_j}{M_{max}}\right)*\frac{\pi}{2}\right)+\delta \tag{28}$$

$$c_2=\sigma*\cos\left(\left(1-\frac{M_j}{M_{max}}\right)*\frac{\pi}{2}\right)+\delta \tag{29}$$

where σ and δ are the constants (σ=2, δ=0.5)

Using this optimization algorithm, a set of non-dominated solutions called Pareto-Front (PF) will be found. Therefore, another method is required to select the compromising solution. A Fuzzy decision-maker can perform that selection. This technique uses membership function for each member of PF via the following formula:

$$\mu_i=\begin{cases}1 & F_i\leq F_i^{min}\\ \frac{F_i^{max}-F_i}{F_i^{max}-F_i^{min}} & F_i^{min}\leq F_i\leq F_i^{max}\\ 0 & F_i^{max}\leq F_i\end{cases} \tag{30}$$

Using the min-max method, the compromising solution can be selected.

The flow chart of the proposed method for solving RBORPD is depicted in Fig. 5. After capturing the snapshot of the system, the status of the network components is determined. Then, economic dispatch is performed to calculate the economic generation of the plants and calculate P. After initializing the optimization algorithm and setting the control variables F2 is calculated in the base case for all load and wind scenarios. Then, the contingency analysis is performed and F1 is calculated. If the number of scenarios and contingencies are terminated, the population is updated and the algorithm will be continued until termination is reached.

4. Simulation results

In this section, the system under study and the necessary data for calculating cost functions are introduced in sub-sections. Then the method is applied to the test systems using different scenarios. To confirm the proposed method, the results are compared with those of the previously published literature.

4.1. System under study

The proposed method is applied on the IEEE 30-bus system. Matpower Version 6 is used for system data and power flow simulation [31]. The 30-bus standard test system is modified by installing 56 MW DFIG wind farms in bus 20. The system data is available in Appendix II. The algorithm is coded in MATLAB R2017a and applied on a core-i5 laptop with a 2.6 GHz processor and 6.0 GB of RAM. Necessary parameters for calculating active and reactive power costs of generators are presented in Table II [19]. The tap ratios are assumed to be within [0.9, 1.1]. The simulated contingencies are the outage of lines 1-2, 2-4, 6-4, 4-12, 12-16, 24-25 and the generator installed on bus 8. Weibull distribution parameters c and k are assumed to be 8 and 2, respectively [32].

4.2. Scenarios

To examine the proposed method, three scenarios are investigated as follows:

1. The proposed possibilistic-probabilistic risk index is compared to the common product method.
2. ORPD with considering wind speed and load forecast uncertainties, VSI and system loss as F1 and F2.
3. RB-ORPD, considering wind speed and load forecast uncertainties using the proposed method.

4.2.1 Scenario 1: Comparing the proposed risk index with the common product method

In this scenario, the proposed possibilistic-probabilistic risk index is compared to the product method. First, Table III compares the results for the cases with high/zero impact and probability.

In the cases where Impact = 0, the risk index is 0 for both methods. This is reasonable because when there is no violation, risk cannot be defined. When the impact is maximum but the probability is zero, the risk is zero in the product method. It is noticeable that severe events like blackout or voltage instability event leads the impact to reach 1. FOR=0 means that this has not yet happened. However, considering equipment fatigue, weather condition, etc. the real probability of these events may be considered as rare, but not zero. In the proposed fuzzy method, the risk of such events is calculated as a medium risk event which must be taken into consideration. For the case with impact and FOR=0.5, the result of risk calculation in the proposed method is also more compatible with practical criteria and the operator's sense about the risk of the events. Moreover, the proposed risk index better reflects the risk of events with high consequence and lower probability compared to the product method.

In addition, for further investigations, it is assumed that impact and probability follow normal PDFs with an average of 0.5. Then, using Monte Carlo Simulation (MCS), 10,000 points were generated from PDFs to estimate the average calculated risk. Figs. 6 and 7 show the histograms of the proposed possibilistic- probabilistic and those of the product methods, respectively. As it is clear from Figs. 6 and 7, the proposed method better estimates the risk because when the average of the impact and probability are 0.5 (median), it is expected that the average of the estimated risk approaches 0.5. The average estimated risks for the proposed method and the product method are 0.5033 and 0.2978, respectively. Therefore, using the product method for estimating the risk may result in underestimating the risk. Consequently, wrong preventive or corrective actions may be taken by the operators. In addition, the estimated risk using the proposed method makes sense for the operators because it is consistent with the operators' experience and the operating criteria.

4.2.2 ORPD with wind and load uncertainty, considering VSI and power system loss as F1 and F2.

This scenario is performed to compare the results obtained by the MOPSO with sine and cosine acceleration coefficient to other algorithms and literature. The risk is not calculated, F1 is assumed to be the expected value of L-Index, and F2 is the expected Ploss that should be minimized. Table IV shows the obtained scenarios using PEM and Table V shows the obtained results. The weighting factors for the scenarios are 0.1743, 0.1810 0.1518, 0.2130, 0.2799. The VSI for the proposed method ranges from 0.102 to 0.14, and the expected power system loss ranges from 3.16 to 4.2 MW. The results demonstrate the superiority of the proposed method in the diversity of solution and objective minimization. The simulation time for a population size of 60 and 100 iterations is about 0.1 [2]. Also, MOPSO is a faster algorithm compared to NSGA-II. Fig. 8 shows the pareto-front for this scenario.

4.2.3 RB-ORPD considering wind and load uncertainty using the proposed method

In this scenario, the proposed method (RB -ORPD) is investigated. This scenario is divided into three cases with different risk levels that can be tolerated by the operators.

Case 1:

In this case, the proposed method is studied according to the flowchart presented in Fig. 5 with maximum risk-level tolerated by the operators. This risk level is set to 0.5 for this case (medium risk level). The obtained results are available in Table VI for this case. The voltage instability risk (F1) varies from 0.57 to 0.595 with an average of 0.5817, and the operational cost (F2) ranges from 34.8 to 61.79 $ with an average of 45$ for the 30-bus test system. It is evident from the results that the average voltage F1 and F2 are decreased by 20% and increased by 4 % compared to the security-based planning (the case without considering the probability of events), respectively. The initial voltage instability risk was 0.78. So, the proposed method could increase system security by decreasing voltage instability risk while improving the system economy simultaneously. The optimal decision variables of the compromising solution are available in Table VII.

Case 2:

In this case, the tolerated risk level is decreased to 0.3. This threshold limits the tolerated contingencies to the low-risk events. Table VI shows the obtained results for this case. Compared to the first case, for the IEEE 30-bus system, the average risk index and the operational cost reach 0.5819 and 48.2, which means 0.03% and 7% increase, respectively.

Case 3*:*

In this case, the risk level threshold is set to 0. It means that risk indexes are calculated but no risk will be tolerated. Table VI shows the obtained results. The average risk index and the operational cost reached 0.584 and 49 $, respectively. This means a 0.51 % and 8.8% increase of risk index and F2, respectively, as compared to Case 1. Therefore, it can be concluded from the results that, on the one hand, if the operators tolerate more risk levels, they can get better performance about system economy and the continuity of serving the consumers can be preserved. On the other hand, the system security level may be decreased. Therefore, an optimal value of risk level tolerated by the operators must be found to guaranty the network security and economy.

However, the result shows that there is no significant difference between thresholds 0.3 and 0.5 for the IEEE 30-bus test system. Yet, threshold 0.3 will limit the risk of events to the low-risk contingencies. Thus, 0.3 might be preferable for the tolerated risk level.

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5. Conclusion

In this paper, the techno-economical risk-based optimal reactive power dispatch method in the wind generator integrated system was presented. Using probabilistic and Delphi-fuzzy method, a new hybrid probabilistic-possibilistic risk index was proposed and considered as the technical objective optimization problem. The load and wind turbine energy uncertainties were modelled in the formulation of the problem. Different relaxation levels for the problem constraint were studied to investigate the effect of risk-taking of the operators on the system's security and economy as well as the continuity of serving customers. The obtained results confirmed the following:

1- Due to low probability of events in the power systems, employing the conventional product method may lead to the underestimation of the risk index. However, the proposed method could help overcome this shortcoming. As a results, wrong preventive or corrective actions may be taken by the operators.
2- The results point to the superiority of the proposed method compared to the previously published methods in objective minimization for solving ORPD problem. In addition, the solutions in Pareto Front found by the proposed method were better distributed as compared to the references.
3- Security-based planning was over-conservative since the probabilities of the events are not taken into account. As a results, it decreases the system economy due to fact that the resources are spent on non-probable events. In contrast, risk-based planning that combines the consequence and probability of events may increase not only the security of the system but also its economy.
4- The more risk-taking ability of the operators led to the higher economic efficiency of the system.

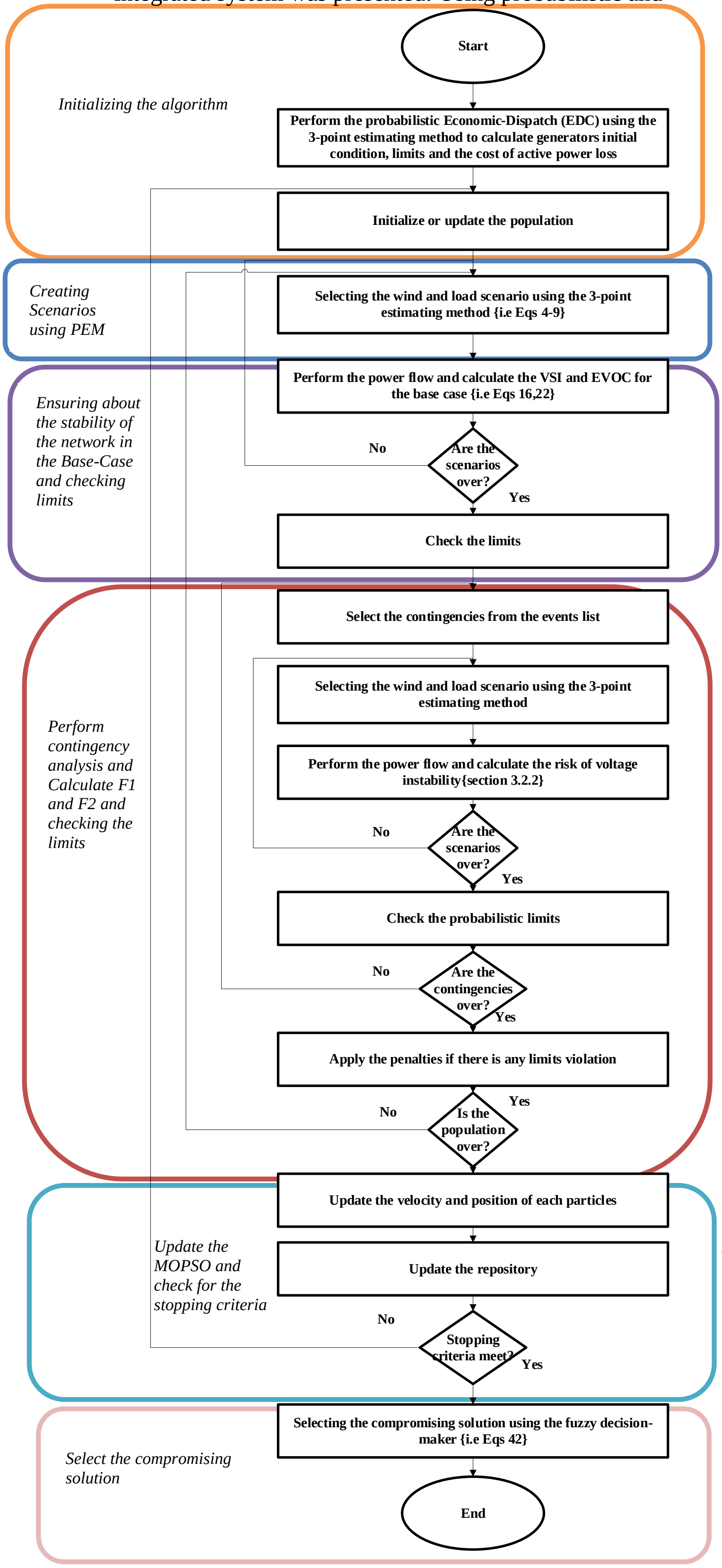

Fig. 5. The flowchart of the proposed method

Table II. Cost parameters of the generators

Generator	ap	bp	cp	aq	bq	cq
G1	0.02	2	0	0.0084	- 0.00075	0.2
G2	0.0175	1.75	0	0.007	- 0.00322	0.84
G3	0.0625	1	0	0.0073	- 0.00344	0.89
G4	0.00834	3.25	0	0.0073	- 0.00344	0.89
G5	0.025	3	0	0.0073	- 0.00344	0.89
G5	0.025	3	0	0.0073	- 0.00344	0.89

Table III. Comparing risk index for fuzzy and product methods

Impact	FOR	Fuzzy risk index	Product method
0	0	0	0
0	1	0	0
1	0	0.5	0
1	1	1	1
0.5	0.5	0.5	0.25

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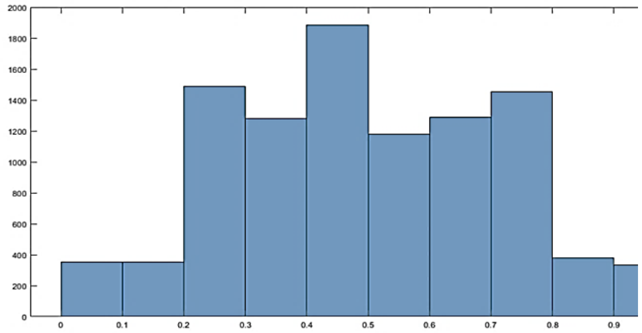

Fig. 6. The histogram of the risk calculated using proposed method

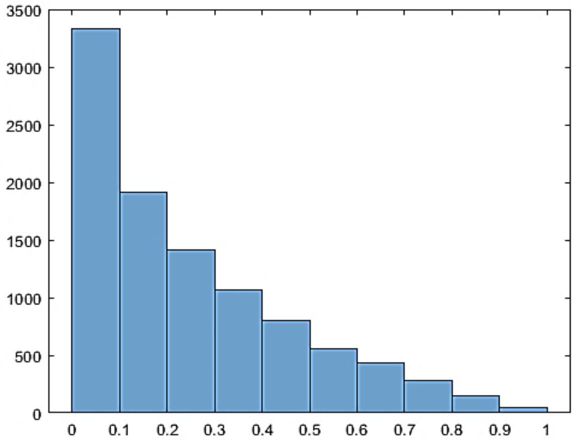

Fig. 7. The histogram of calculated risk using the poduct method

Table IV. Scenarios generated for wind speed and load forecast uncertainties

Scenario Number	Wind speed (m/sec)	Load (p.u)
1	11.3128	1.026
2	5.5214	1
3	1.5269	0.973

Table V. Comparison of the proposed method with published references

	EL-Index	Expected power system loss (MW)	Time (sec)
Reference [2]	0.0939 - 0.17	3.74-4.082	4000
Reference [9]	0.1192-0.1317	4.55-7.07	-
Reference [14]	0.111-0.121	4.4-6.6	-
Reference [23]	0.1161-0.1258	3.4815-4.0646	-
Proposed method	0.102-0.145	3.16-4.09	406

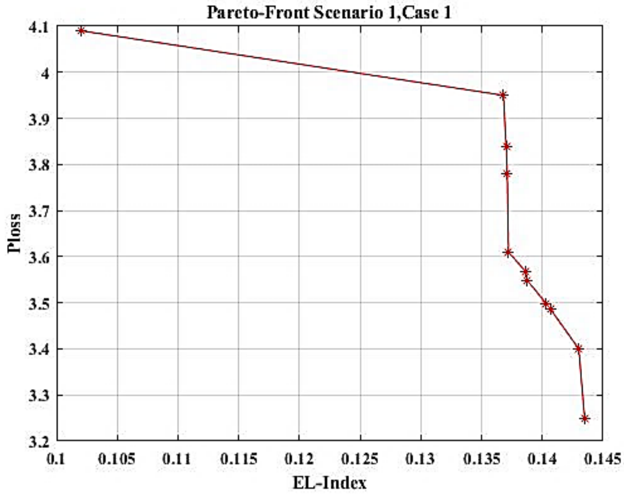

Fig. 8. Pareto-Front for the scenario II

Table VI. The results for the scenario III

	F1	F2 ($)
Security based planning	0.744-0.703	76.8-43.65
Case 1	0.595-0.57	61.79-34.8
Case 2	0.593-0.571	57.25-38.09
Case 3	0.6-0.563	90-31

Table VII. Optimal decision variables for scenario III

Generator	Expected economic active power (MW)	Vschedule (P.U) Case 1	Vschedule (P.U) Case 2	Vschedule (P.U) Case 3
G1	42.17	1.023	1.038	1.0460
G2	55.32	1.018	1.012	1.0298
G3	13.73	1	0.986	0.9871
G4	21.5	0.97	1.013	1.013
G5	13.7	1.04	1.038	10396
G6	26.2	1.05	1.033	1.03
Gwind	27.04	0.97	0.995	1.025
Capacitors	Case 1	Case 2	Case 3	-
C1	2.3	0.4838	0.6544	-
C2	0	0.9971	0.6853	-
C3	0	1	1	-
C4	1.5	1	0.4337	-
C5	0	0.3700	0.9517	-
C6	4.4	0.8401	0	-
C7	3.8	0.3204	0.5695	-
C8	2	1	0.1728	-
C9	4.6	0.7830		-
Transformers	Case 1	Case 2	Case 3	-
T1	0.93	1.0131	0.9886	-
T2	0.90	1.0128	1.0169	-
T3	0.9	0.9870	0.9748	-
T4	1	1.0133	0.9811	-

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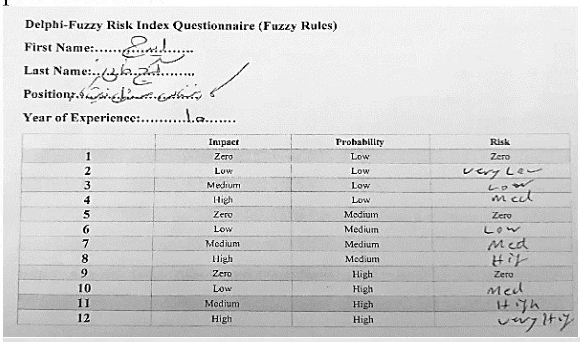
7. Appendix I

10 Iranian national grid operators were asked to fill out the questionnaire about risk quantification. They must express their opinion about voltage instability risk, force outage rate and voltage stability margin limits using Delphi- Fuzzy method. Some of the questionnaires are presented here.



Delphi-Fuzzy Risk Index Questionnaire (Fuzzy Rules)

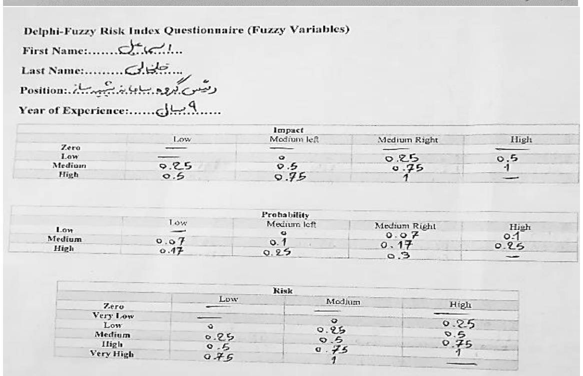
First Name:......[illegible]......

Last Name:......[illegible]......

Position:......[illegible]......

Year of Experience:..........۱۵.......

	Impact	Probability	Risk
1	Zero	Low	Zero
2	Low	Low	very Low
3	Medium	Low	Low
4	High	Low	Med
5	Zero	Medium	Zero
6	Low	Medium	Low
7	Medium	Medium	Med
8	High	Medium	High
9	Zero	High	Zero
10	Low	High	Med
11	Medium	High	High
12	High	High	very High



Delphi-Fuzzy Risk Index Questionnaire (Fuzzy Variables)

First Name:......اسماعیل......

Last Name:......[illegible]......

Position:......[illegible]......

Year of Experience:......۹ سال......

Impact	Low	Medium left	Medium Right	High
Zero	—	—	—	—
Low	—	0	0.25	0.5
Medium	0.25	0.5	0.75	1
High	0.5	0.75	1	—

Probability	Low	Medium left	Medium Right	High
Low	—	0	0.07	0.1
Medium	0.07	0.1	0.17	0.25
High	0.17	0.25	0.3	—

Risk	Low	Medium	High
Zero	—	—	—
Very Low	—	0	0.25
Low	0	0.25	0.5
Medium	0.25	0.5	0.75
High	0.5	0.75	1
Very High	0.75	1	—

8. Appendix II

IEEE 30-bus test system includes 30 buses, 6 generators, 41 branches, 9 capacitors and 4 transformers. The slack bus is located at bus 1. Four branches, 6-9, 6-10, 4-12 and 28-27 are under load tap changing transformers. Buses 10, 12, 15, 17, 20,21, 23, 24 and 29 are selected as shunt VAR compensation buses.The test system is modified by installation of a 56 MW DFIG wind farm at bus 20. The data of the DFIG generators are taken from 2.5 MW Nordex DFIG wibd turbines.

Nomenclature			
$N_{T\text{-}Line}$	number of T-Lines	Q_c	reactive power of compensators in Mvar
N_g	number of generators	P_w	active power of DFIGs in MW
Nb	number of buses	Q_g	reactive power of the generators in Mvar
g	generator	σ	standard deviation of input variable
w	Wind Farm	μ	Average of input variable
i, j	index of bus	M	number of the input random variables of the PEM
m	random input variable of the PEM	Y	admittance matrix
k	estimated location for the input random variable	g	line conductance
λ	failure rate (failures/year)	a_g^p, b_g^p, c_g^p	active power fuel cost coefficients
μ	repair rate (repair/year)	a_g^q, b_g^q, c_g^q	reactive power cost coefficients
x	state variable vector	W_i	weighting factors
u	decision variables vector	P_{D_i}	active power of load bus i in MW
P_{loss}	power system loss	Q_{D_i}	reactive power of load bus i in Mvar
EVOC	expected value of operational cost	Q_{slack}	reactive power of the slack bus in Mvar
P_{slack}	active power of the slack bus in MW	P_{gi}	active power generated by the generator i
Q_w	reactive power of DFIGs in Mvar	Q_{D_i}	reactive power of load bus i in Mvar
P_{wind}	output power of wind generator		
V_L	voltage of load buses	F1	first objective function
V_g	voltage terminal of generators	F2	second objective function
T_p	tap ratio of transformers	L_{index}	Voltage Stability index
δ	voltage phase of the sending and receiving end of each line	LC	active power loss cost of the network in $
S_{li}	apparent power of flowing through each line	P	price of active power loss in $/MW
c	scaling parameter of the wind function	FC	fuel cost in $
k	shape factor of the wind function	C_q	reactive power cost of the generators in $

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v	wind speed in m/s	$P_{gen-tot}$	total active power generated by the all generators
$v_{cut\text{-}in}$	cut-in speed of wind turbine in m/s	$P_{load-tot}$	total demand
$v_{cut\text{-}out}$	cut-out speed of wind turbine in m/s	$Q_w^{max\text{-}stature}$	reactive power limit of DFIG due to stator current
v_{rate}	rated wind speed in m/s	$Q_w^{max\text{-}rotor}$	reactive power limit of DFIG due to rotor current
U	unavailability of any power system components	γ_w	power factor angle of the DFIG
A	availability of any power system components	$Q_g^{max\text{-}field}$	maximum achievable reactive power due to the field current limit
$Q_g^{max\text{-}armature}$	reactive power limit of DFIG due to armature current	S-RISK	flow violation risk
VSI-RISK	voltage Instability risk	V-RISK	voltage violation risk