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Risk-Cost Minimization in Optimal Reactive Power Dispatch Problem in the DFIG Integrated System

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ABSTRACT

Objective: In this paper, a novel method for a multi-objective and risk-based optimal reactive power dispatch is proposed. The method includes two main objective functions: technical and economic. The technical objective involves minimizing the risks of voltage instability, voltage deviation, and flow violation, and the economic objective involves minimizing the costs of reactive power generation, active power losses, load shedding, and active power rescheduling. Using these functions and assigning different weighting factors for each sub-objective, the risk of the events or uncertainties to customers or the grid can be managed. In addition, moment matching is used to discretize and create scenarios from continuous probability distribution functions of wind speed and electrical energy uncertainties. As the number of uncertain variables increases, so does the number of scenarios and the simulation time. Therefore, the fast-forward selection algorithm is applied to reduce the number of scenarios. To reduce the computational complexity and the number of topological scenarios, a new contingency filtering method based on high-risk events is proposed. A modified multi-objective PSO algorithm based on a hybrid PSO with sine-cosine acceleration coefficients is proposed to find the Pareto front of solutions. The method is implemented on the modified IEEE 30-bus test system. To demonstrate the effectiveness of the proposed method, the results are compared with previously published literature. The results show that risk-based scheduling increases system reliability and cost-effectiveness compared to traditional scheduling.

NOMENCLATURE

fr Failure rate of the component per year
rr Repair rate of the component per year
k Shape factor of Weibull distribution
c Scaling parameter of Weibull distribution
v Wind speed (m/sec)
$a_{gi}^{q}, b_{g}^{q}, c_{gi}^{q}$ Reactive power cost coefficient
g_{k}, B_{k} Conductance and suseptance of the line
i,j Bus i and event j
S Scenario number
VIR, VVR, FVR Voltage instability risk, Voltage violation risk, flow violation risk
VSM Voltage stability margin
V_{min} Minimum voltage of the network
SL_i Apparent power of line i
P Average active power price in $/MW
PF Participation factor of the generators
$NC, n_{stage}, n_{lc-load}$ Number of contingencies, number of SPS stages, number of load cut performed
OFV, IF Objective function value, importance factors of the sub-objective functions
N.OUT Number of outputs
EV, ER Emergency voltage limit, Emergency rating of the line

I. Introduction

A. Research Motivation

Optimal Reactive Power Dispatch (ORPD) is a special form of Optimal Power Flow (OPF) that deals with reactive power instead of active power. The objective of this optimization problem is to find the optimal value of reactive power resources in the system to improve security and economic efficiency. Hence, it is one of the most principal problems in power systems. However, system security is usually compromised after an event.

To ensure system security during events, it is essential to simulate contingencies in the planning phase (a preventive or corrective approach). When contingencies are simulated, the problem is treated as a security constraint OPRD (SC-ORPD). The SC-ORPD, which is a deterministic method, has been used by independent system operators (ISO) for several years because of its high reliability and simplicity. Operational and security constraints must be met before and after contingencies. However, deterministic approaches are often too conservative and therefore not economical (especially in preventive planning), since they are based on the most severe events [1]. Therefore, the use of these methods is less and less considered by operators and researchers nowadays.

In addition, the installation of renewable energy sources (RESs) in power systems has recently increased due to environmental issues. It has been shown that the deterministic modelling of renewables can lead to voltage instability and power flow fluctuations due to their intermittent nature. Demand uncertainty due to load forecasting errors is also unavoidable. Demand uncertainty also affects power system planning, security, and economics. Therefore, these uncertainty parameters must be efficiently considered in the planning and operation phases to ensure system security and economics.

Recently, the risk-based ORPD (RB-ORPD) has received more attention because of its ability to address the above issues. The risk indices quantify the system stress and can be formulated using the probability and consequence of the events or the uncertainties (usually the production of probability and consequence). These functions can be calculated based on the impact of the events on the customers or the transmission system.

It is worth noting that risk-based methods are so efficient that can not only increase system safety (by taking into account contingencies or uncertainties of the system in problem formulation) but also increase system efficiency (due to allocation of resources to high consequence and probability events rather than only to high consequence ones).

However, reducing system risk leads to an increase in operating costs (these are conflicting goals). Therefore, for ORPD or OPF problems, a comprehensive techno-economic objective function must be considered to ensure the reduction of system or customer risk and operating costs. The objective function should include all or some of the various system risks (risk of voltage instability, risk of voltage violation, etc.), customer risks (loss of load expectancy, loss of load frequency, etc.), and operating costs (cost or price of active or reactive power generation, system losses, etc.).

Furthermore, if scheduling is expected to be implemented with minimal deviation in the control centers of the power system, the practical limitations of the sources and control systems must be included in the formulation of the ORPD problem. Thus, the problem must be subjected to various practical and mathematical constraints.

Considering the previously mentioned objectives and constraints, the ORPD is difficult to solve. From the point of view of solving the optimization problem, the ORPD is a nonlinear and nonconvex problem with many constraints. Many traditional optimization methods have been presented in the literature to solve this problem. However, these methods are trapped in local optima, and some depend on the initial estimation of the variables and do not provide much freedom in choosing the objective functions and the different constraints. Therefore, metaheuristic methods and evolutionary algorithms can be used in this area.

B. Literature Review

The ORPD problem has been addressed in several research studies. In [2], a new corrective voltage control (CVC) for power systems is presented. The uncertainty of wind power generation and demand values is considered in the problem formulation through a scenario-based approach. Moreover, the participation of demand-side resources is considered an effective control option to reduce the control cost. [3] presents a novel stochastic preventive voltage control, ORPD. Wind speed uncertainty is considered in this reference and a scenario-based modelling approach is used to discretize the continuous PDF of uncertain variables. The risk associated with each objective function is calculated using the conditional value at risk (CVaR). In [4], a new criterion for real-time estimation of "N-1" system risk is presented. The risk is calculated using the product of probability and impact. In [5], a probabilistic optimal power flow considering wind uncertainty is presented. The objectives of the presented method are to minimize the expected generation cost and the downside risk. In [6], a framework with weighted random constraints based on optimal power flow is presented. The uncertainty of the wind power forecast is taken into account in this reference.

In [7], the authors propose a new framework for stochastic OPF. The framework can balance the generation cost and system risk. In [8], a novel scenario-based method for avoiding voltage instability under wind and load uncertainty is presented. In [9], the optimal placement and sizing of the static var compensator (SVS) are presented to minimize the risk of short-term voltage stability after the occurrence of events. The objective functions are to minimize the investment cost of

SVC and the risk of short-term voltage instability. The problem is solved using a genetic algorithm. The paper considers the effects of DGs and the customers' dynamic load model. However, the effects of the uncertainties of DG are neglected.

In [10], coordinated optimization of reactive power reserve, stochastic and multi-objective optimal power, and reactive power management are presented. Economic objectives and an increase in the load margin are considered objective functions to minimize. In [11], a techno-economic algorithm for SC-ORPD is presented, which considers the uncertainty of wind and demand. MCS is used to incorporate stochastic parameters, and NSGA-II is used to find non-dominant solutions. In [12], a method for calculating probability densities of the voltage level is presented. For this purpose, the problem is integrated with an ORPD that takes into account the uncertainty of active power generation. In this work, the probability densities are handled with MCS and used as soft constraints for an ORPD problem. In [13], the ORPD problem with minimizing the loss, voltage deviation, and increasing the voltage stability margin is presented. The problem is formulated as a mixed-integer nonlinear optimization problem that contains both discrete and continuous decision variables. The Artificial Bee Colony (ABC) algorithm is used to solve the problem.

In [14], a risk-based distribution robust optimization problem is proposed to balance the operational cost and risk in the real-time framework. In this reference, the presented method takes into account the voltage reliability of the buses even if the PDF of the uncertain variables cannot be estimated accurately. [15] The Rao-3 optimization algorithm is used to solve the constrained ORPD problem. In addition, the uncertainties of solar and wind energy as the most commonly used technologies in electric power systems and the uncertainties of demand forecasting are exploited in this work.

In [16], the Multi-Objective ORPD in a distribution network is presented for minimizing the active power loss, voltage deviation, and cost of reactive power compensators. In this paper, the effects of different load models on the cost functions are studied and a modified Grey-Wolf optimizer is used to solve the problem. In addition, the effects of installing DGs in the grid are investigated. However, the uncertainty of the DGs' power generation is ignored.

In [17], the effect of coordinated and automatic voltage regulation in a power system with wind turbines and SVC is presented. The objective function is mainly formulated as a single-objective reactive power optimization problem. In [18], the solution to the ORPD problem by the combined optimization method of particle swarm and various individual evolution is presented. The objective function of minimizing the active and reactive power losses of the network is considered. The obtained results were compared with the results of the PSO method.

The Multi-Objective SC-ORPD considering the technical uncertainties of power systems is presented in [19]. Maximizing the voltage stability margin based on the new voltage instability risk index and minimizing the losses are the objective functions. The SPEA-II optimization algorithm is then used to solve the problem. In [20], a novel risk-based ORPD algorithm with technical and economic objectives in a wind-integrated system is presented. The proposed method is more compatible with operational criteria. In this reference, a novel probabilistic-possibilistic risk index for risk quantification is presented.

In Table 1, the studied references are categorized according to their objective functions, risk-based or security-based planning, and their problem-solving algorithm. In Table 1, 68% of the studied works considered the problem as a multi-objective problem. 26% of the references considered contingencies in their problem (security constraint) and 47% of the references solved the problem with a risk-based formulation. It is noteworthy that, the contingencies are the main factors of the system risk. Thus, the subscription of the third and fourth columns shows the references that solved the problem using a risk-based formulation, and the risk is estimated after simulating the contingencies. Only 20% of these references belong to this category. 15% of the references consider all technical contingencies, including events, renewables, and load forecast contingencies. Finally, 52% of the references use a meta-heuristic algorithm to solve the problem.

C. The Necessity of Research

Based on the literature review and the results of Table 1, several existing gaps were identified, including:

1. A comprehensive objective function that risk and operational cost can be managed by ORPD or OPF simultaneously is not considered in the references.
2. The simultaneous consideration and management of the impact of risks arising from unplanned events or uncertainties on the power system and customers.
3. All technical uncertainties including RESs, load forecast, and contingencies are not studied in reviewed papers.
4. A contingency filtering method based on the riskiest events needs to be proposed. The proposed algorithm should be able to eliminate the influence of the control variables changing and updating during the optimization process.
5. PSO is a well-known, efficient and fast method in many engineering optimizations and planning. However, its premature convergence, lack of diversity, and being trapped in locally optimal solutions are mentioned as the shortage of this algorithm. Other optimization algorithms like NSGA and SPEA are accurate but with slow convergence.
6. *Novelty and main contribution*

   To address these issues, in this paper, a novel risk-based ORPD method is presented. The contributions of the are:

TABLE 1
COMPARING REFERENCES

Reference number	Multi-Objective	Security Constraint	Risk Based	All technical uncertainties	Meta-Heuristic
2	✓	×	×	×	×
3	×	×	✓	×	×
4	×	✓	✓	×	×
5	✓	×	✓	×	✓
6	✓	×	✓	×	×
7	✓	×	✓	×	×
8	×	×	×	×	×
9	✓	×	×	×	✓
10	✓	×	×	×	×
11	✓	✓	✓	✓	✓
12	×	×	×	×	✓
13	✓	×	×	×	✓
14	✓	×	✓	×	×
15	✓	✓	×	×	✓
16	✓	×	×	×	✓
17	×	×	×	×	×
18	×	×	×	×	✓
19	✓	✓	✓	✓	✓
20	✓	✓	✓	✓	✓

1- To cover 1 and 2, a comprehensive technical-economic objective function is proposed. The technical objective consists of voltage instability risk, voltage violation risk, and current flow violation risk, and the economic objective includes generator reactive power generation/absorption cost, active power loss, cost, load shedding cost, and generation compensation cost. The proposed method is a hybrid preventive-corrective approach.

The proposed method finds the optimal decision variables of generators, compensators, and transformers in such a way that there is no violation after the occurrence of uncertainties in the system. If this is not possible or costly, remedial actions (manual by the operators or automatic by the special protection systems) are performed after the occurrence of violations following a fault. In this way, the risks to the system (voltage instability, voltage violation, and power flow violation risks) and the risks to the customer (loss of load maintenance) can be simultaneously minimized or managed by assigning different important factors to the sub-objective functions by the operators or planners, depending on the network condition, system reactive power reserve.

Moreover, the operating limits of conventional and wind generators are considered in the problem formulation to increase the practicality of the proposed method.

2- To solve Problem 3, the uncertainties imposed on the system by the integration of renewable energy (doubly fed induction wind generators (DFIG) in this work), the uncertainty of load forecasting, and the probability of accidental equipment failure are included in the problem formulation of the proposed method by using a probabilistic approach to estimate the risk. For this purpose, the moment matching method (MMC) is used to generate optimal scenarios considering uncertain variable statistics. To reduce the size and select the best scenarios, the Fast Forward Selection (FFS) algorithm is used.

3- A new contingency filtering method to cover issue 4, is proposed that finds high risky contingency while considering the effect of the decision variable changing during the optimization procedure. In fact, the proposed method is integrated into the optimization process which is different from the usual methods that filtering is done before the optimization procedure is run.

4- To address 5, Hybrid Multi-Objective PSO with sine cosine acceleration coefficients (H- MOPSO-SCAC) is introduced and utilized based on H- PSO-SCAC to achieve Pareto-front of the solutions.

D. Organization of the Paper

The paper is organized as follows: Section II is devoted to the methodology. Subsection A describes how to model the random outage of the branches, wind and demand uncertainties, and scenario generation and reduction method using MMC and FFS, respectively. Subsection B presents, the proposed multi-objective risk-based ORPD. In subsection B, objective functions and constraints of the proposed method are described. Subsection C presents the proposed contingency filtering method and subsection D is devoted to a novel H-MOPSO-SCAC description. Section III is dedicated to the test results. First, the detail of the system under study is presented in subsection A. Simulation results are available in subsection B and subsection C is devoted to sensitivity analysis. Section IV is devoted to the conclusion.

II. Methodology

A. Power System Uncertainty Modelling

The operation and planning of power systems involve uncertainties. Loads, renewable resources, and random outages are the main sources of uncertainties in the grid. The probabilistic security assessment is a leading approach for dealing with these uncertainties and calculating the risk indices they cause. In this approach, the continuous probability distribution functions (PDF) of random variables are discretized using a limited number of scenarios. Then, the deterministic analysis is performed separately for each generated scenario and the expected values of the outputs are calculated.

1. Random Branch Outage Probability

The two-stage model, which represents a well-known approach to calculating the random probability of failure of the component, is used in this work [21]. In this model, the equipment can be in one of the states "in service" (available) or "out of service" (unavailable). The average unavailability of the equipment in a long-term time frame is calculated using [21]:

$$FOR=\frac{\mathrm{fr}}{\mathrm{rr}+\mathrm{fr}} \tag{1}$$

The failure rate (FOR) can be used to estimate the failure probability of the random component.

2. *Modelling the Uncertainty of Wind Turbine Energy*

The energy generated by wind turbines is highly dependent on the wind, which fluctuates [12, 13]. It has been shown that deterministic modelling of fluctuating wind generators can lead to system instability. The most common PDFs for modelling wind speed uncertainty are Weibull or Rayleigh PDFs [23]. In this work, the Weibull PDF is used:

$$f(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left(-\frac{v}{c}\right)^{k} \quad (2)$$

In this work, a linearized characteristic curve is also used to represent the relationship between turbine output power and wind speed. The data of the characteristic curve are available in [11].

3. *Demand Uncertainty Modelling*

Demand uncertainty due to load forecasting errors is usually estimated using the normal probability distribution function (PDF) [2]. In this paper, the mean of the normal PDF is assumed to be the forecast load, and the standard deviation is set to 3% [19].

4. *Scenario Generation and Reduction*

It is challenging to solve stochastic models that contain variables with continuous distribution. In such cases, a discretization process (scenario generation) is used to estimate the continuous PDF of the uncertain variable with a limited number of scenarios. However, in most cases, it is difficult or impossible to find the exact probability density function of random variables. Nevertheless, it is possible to approximate the continuous distributions using their statistical properties. Therefore, in this paper, the moment matching method (MMC) was used to create a limited number of scenarios. This method uses statistical properties instead of exact PDFs of the uncertain variables [22]. For this purpose, an optimization problem is defined that minimizes the distance between the statistical properties of the continuous and matched discrete distributions. The optimization problem is subject to the constraint that the sum of the relative importance of the statistical specifications (mean, variance, kurtosis, and skewness in this work) equals one. The MMC method is described in Appendix A.

However, increasing the number of uncertain variables leads to an increase in the number of scenarios and thus in simulation time. In this case, a strategy is needed to reduce the number of scenarios. This is done by selecting a subset of scenarios that represents the entire scenario (scenario reduction). Fast Forward Selection (FFS), a well-known algorithm for scenario reduction, is used in this work. The FFS procedures can be found in [22]. MMC is used to create 5 scenarios for wind speed and load forecasting (total number of scenarios= $[5]_{1*5}$* $[5]_{5*1}$). Then 6 scenarios are selected as reduced scenarios using FFS. Table 2 shows the reduced scenarios and their corresponding probabilities.

B. *Proposed Multi-Objective Risk-Based ORPD*

The general formula of the proposed risk-based ORPD with multiple objectives is presented in (3), which contains techno-economic objective functions (F1 and F2, respectively) that must be minimized under equality and inequality constraints (A, B).

$$\min\begin{cases}F1(vs,vc)\\F2(vs,vc)\end{cases}$$

$$\text{s.t}$$

$$A(vs,\ vc)=b,$$

$$B(vs,\ vc)>0, \quad (3)$$

where, F_1 and F_2 are formulated as:

$$F_1=w_{11}*F_{11}+w_{12}*F_{12}+w_{13}*F_{13} \quad (4)$$

$$F_2=w_{21}*F_{21}+w_{22}*F_{22}+w_{23}*F_{23}+w_{24}*F_{24} \quad (5)$$

Where, vs is the vectors of state variables, vc is the vector of control variables, w_{ij} are importance factor of sub-objective functions that are factors are assigned proportionally to the relative importance of each sub-objective and the different operational strategies. F11, F12, F13, F21, F22, F23, F24 are sub-objectives of technical and economical objective functions, respectively.

The vs and vc can be expressed as follows:

$$vs=[P_{slack},\ Q_{slack},V_L,Q_g] \quad (6)$$

$$vc=[\ V_g,Q_c,T_p,P_w,Q_w] \quad (7)$$

where, $P_{slack},\ Q_{slack}$ are active and reactive power of slack generator, V_L is the voltage of PQ buses, Q_g is the reactive power of generators. V_g is the voltage of generators, Q_c is the reactive power of compensators, T_p is the tap ratio of transformers, $P_w,\ Q_w$ are the active and reactive power of wind generator, respectively.

1. *Voltage Instability Risk (F_{11})*

In most references, the risk index is quantized by the production of the consequence and probability of the events or uncertainties [9, 11, 14, 29]. For practical purposes, a certain level of violation and risk is assumed to be acceptable by the operators (for example, voltage deviation). The L-index which is presented in [23] is used in this paper to estimate the Voltage Stability Margin (VSM) following a contingency. So, using the L-index, a voltage instability risk index is developed which combines the probability and consequence of the events if VSM decreases from a pre-specified amount.

The index will become zero when an acceptable stability margin is achieved and otherwise increases linearly with decreasing VSM as follows:

$$VIR=\begin{cases}\sum_{n_l=1}^{n_l}\sum_{s=1}^{s_n}\frac{(L_i-VSM)}{L_{max}}*FOR_j & if\ L_i>VSM\\ 0 & if\ VSM>L_i\end{cases} \quad (8)$$

TABLE 2
SCENARIO REDUCTION RESULTS

Wind Speed (m/s)	LOAD %	Probability
0.436	1	0/123
3.52	1/011	0/17
4.7	0/988	0/174
1.283	0/949	0/127
4.7	1	0/226
10.5	1/053	0/18

2. *Voltage Violation Risk (F_{12})*

Similar to the voltage instability risk estimation, the voltage violation risk is calculated as follows:

$$VVR=\begin{cases}\sum_{n_l=1}^{n_l}\sum_{s=1}^{s_n}\frac{(V_i-EV)^2}{V_{min}}*FOR_j & if\ V_i>EV\\ 0 & if\ EV>V_i\end{cases} \quad (9)$$

3. *Flow violation Risk (F_{13})*

The flow violation risk can be calculated:

$$FVR=\begin{cases}\sum_{n_{br}=1}^{n_{br}}\sum_{s=1}^{s_n}\frac{SL_i-ER_i}{SL_i^{pre}}*FOR_j & if\ S_i>ER\\ 0 & if\ ER>S_i\end{cases} \quad (10)$$

4. *Reactive power cost (F_{21})*

Reactive power cost is due to increasing winding losses caused by the generation or absorption of reactive power by the generators, as well as the opportunity cost. The quadratic cost function can estimate reactive power cost as follows [10]:

$$EC_q=\sum_{s=1}^{s_n}\sum_{i=1}^{N_g} a_{gi}^q Q_{gi}^2+b_g^q Q_{gi}+c_{gi}^q \quad (11)$$

5. *Active power loss cost (F_{22})*

The cost of active power loss can be estimated using the following equation [24]:

$$ELC=P^*\sum_{s=1}^{6n}\sum_{k=1}^{N_{T-Line}} g_k[(V_i^2+V_j^2-2V_iV_j cos(\delta_i-\delta_j)] \quad (12)$$

6. *Load Cut Price (F_{23})*

When an emergency occurs, following an event usually, if certain operational limits are violated for a short period, some loads can be manually or automatically cut as a remedial action. Special Protection Systems (SPS) are capable devices to perform automatic load shed in such cases. These devices are designed for multiple stages. The cost of load cut can be expressed as follows:

$$ELSC=\sum_{s=1}^{s_n}\sum_{i=1}^{NC}\sum_{j=1}^{n_{stage}}\sum_{f=1}^{n_{lc-load}} P_jL_f*FOR_{NC} \quad (13)$$

7. *Generation Compensation Cost (F_{24})*

In power system operation, if there is a generator failure or a deviation from the expected power of the wind turbine, the remaining plants must compensate for the active power generation and consumption unbalance to maintain the frequency at its predefined value. In the planning stage, if the imbalance between power generation and consumption of active power exceeds the capability of the slack bus to generate power, the power flow may diverge. The power flow divergence may be considered an instability by mistake. To avoid such situations, the active power imbalance must be compensated in active power unbalance cases. In certain ISO policies, this compensation is paid to the plant with an additional fee. This can be expressed as follows:

$$EGCC=\sum_{s=1}^{s_n}\sum_{i=1}^{NC}\sum_{j=1}^{ng} PF_j*\Delta P*IC_j*FOR_{NC} \quad (14)$$

8. *Power Flow Constraints*

Power flow equations are equality constraints of the OPF problem.

$$P_{G_i}\text{-}P_{D_i}\text{-}V_i\sum_{j=1}^{Nb}V_j\left[G_{ij}\cos\left(\delta_i\text{-}\delta_j\right)+B_{ij}\sin\left(\delta_i\text{-}\delta_j\right)\right]=0 \quad (15)$$

$$Q_{G_i}\text{-}Q_{D_i}\text{-}V_i\sum_{j=1}^{Nb}V_j\left[G_{ij}\sin\left(\delta_i\text{-}\delta_j\right)+B_{ij}\cos\left(\delta_i\text{-}\delta_j\right)\right]=0 \quad (16)$$

9. *Voltage Constraints*

The voltage of the controlled and uncontrolled buses, including wind turbine buses, must be within the highest and lowest limits in the base case.

$$V_i^{min}\le V_i\le V_i^{max} \quad (17)$$

10. *Reactive Power Constraints*

If the reactive power output of the generators exceeds the capability curve range, the bus voltage will become uncontrollable and the bus will be converted from PV to PQ in power flow studies. The operating point, internal voltage, armature current, and reactance of the generators are factors that influence the capability curve of the generators. Using these factors, the capability curve of the generators and wind turbines can be estimated. The formulas for modelling generators and wind turbine capability curves can be found in [11]. They are not provided here to keep the text concise.

11. *Transformer Constraints*

The higher and lower bounds of tap number of transformers are as follows:

$$T_i^{min}\le T_i\le T_i^{max} \quad (18)$$

12. *Shunt Compensators limits*

The VAR generation/absorption of the shunt compensator is limited by its lower and upper bounds.

$$Q_{ci}^{min}\le Q_{ci}\le Q_{ci}^{max} \quad (19)$$

13. *Security Constraints*

Transmission line loadings and voltage stability margin limits must be met in the base case. They can be defined as follows:

$$S_{li}\le S_{li}^{max} \quad (20)$$

$$VSM_i<VSM_{pre-def} \quad (21)$$

C. *Contingency Screening*

The contingency filtering algorithm separates critical events from non-critical ones to be simulated, thereby reducing simulation time. The contingencies from the events list that lead to high risk are considered critical. In the proposed method, the advantage of population-based optimization algorithms will be utilized to perform a sensitivity analysis and filter high-risk contingencies. Indeed, the screening algorithm is integrated into the optimization problem for this purpose and will be updated during the iterations. The advantage of the proposed approach is that it allows for the examination and tracking of the effect of variations in the control variable on the system's security, reliability, and customer satisfaction. The algorithm is as follows:

Step 1: Create the initial contingency list.

Step 2: Create an initial random population.

Step 3: Using the initial contingency list, perform contingency analysis for all population members and identify the events with the highest risk.

Step 4: Eliminate any repetitive events from the list and create a list of critical events.

Step 5: Update the population and continue the optimization procedure with the selected list of critical events.

Step 6: If the optimization iteration reaches the recheck number, replace the critical events list with the initial contingency list.

Step 7: Go back to step 3 and continue until the optimization stop criteria are met.

The list containing high-risky events is replaced by the initial contingency list in certain optimization iterations to check and identify the most severe events with variations in control variables.

D. H-MOPSO-SCAC Optimization Algorithm

PSO is a well-known and efficient method for many engineering optimization and planning problems. The advantages of the PSO method are that it is easy, simple, and can be implemented in any working environment. However, premature convergence, lack of diversity, and being trapped in locally optimal solutions are mentioned as shortcomings of the PSO [25]. To address these limitations, a novel search strategy is proposed that combines the hybrid particle swarm optimizer (H-PSO) with sine cosine acceleration coefficients (SCAC) within the PSO framework and is called H-PSO-SCAC [26]. Based on modifications [26], this paper introduces a modified version of multi-objective PSO (MOPSO) called H-MOPSO-SCAC, which is designed to handle multi-objective problems. These modifications are as follows:

1- Opposition-based learning (OBL) can increase the opportunities of reaching the global optimal solution.

i- Randomize the initial population.

ii- Calculate the reverse population based on (22).

$$X_{max.j} + X_{min.j} - X_{ij} \tag{22}$$

Where, $X_{max.j}$ and $X_{min.j}$ are the population position max and min value at dimension j, respectively, X_{ij} is the population member i and $X'_{ij}$the opposite population.

v- Using domination theory, select the nondominated solution between X_{ij} and X'_{ij} to maintain the population size.

2- The sine map is used to adjust the inertia weights ω of the PSO. The range of the sine map is [0,1]. The inertia weight ω is given as follows:

$$\omega = \frac{c}{4} \sin\left(\pi_{x_{k-1}}\right) \tag{23}$$

Where, k is the current iteration number.

3- A modified update formula for positions in each iteration is used. This modification can improve the exploration and exploitation of the algorithm.

$$X_{i+1}^{d} = X_{i}^{d} * W_{ij} + V_{i}^{d} * W'_{ij} + \rho * gbest^{d} * \varphi \tag{24}$$

Where, W_{ij} and W'_{ij} are the dynamic weights, $gbest$ is the current global best, X_i^d and V_i^d are the previous solution and velocity respectively, ρ random number between 0 and 1, φ is the coefficient that determines the maximum step size.

$$w_{ij} = \varphi = \frac{\exp\left(\frac{f(j)}{u}\right)}{1+\exp\left(-\frac{f(j)}{u}\right)^{iter}} \tag{25}$$

$$w'_{ij} = 1 - w_{ij} \tag{26}$$

Where, u is the mean fitness value in the first iteration, iter is the current iteration and f(j) is the fitness of the jth particle.

4- The sine cosine acceleration coefficients are:

$$c_1 = \sigma * \sin\left(\left(1 - \frac{M_j}{M_{max}}\right) * \frac{\pi}{2}\right) + \delta \tag{27}$$

$$c_2 = \sigma * \cos\left(\left(1 - \frac{M_j}{M_{max}}\right) * \frac{\pi}{2}\right) + \delta \tag{28}$$

Where, σ and δ are the constant (σ=2, δ=0.5)

Fig.1 shows the flowchart of the proposed method and the optimization procedure.

III. TEST RESULTS

A. System Under Study

The proposed method is applied to the modified IEEE 30-bus test system. The test system is modified by installing a 60 MW Doubly Fed Induction Generator (DFIG) wind farm at bus 20. In addition, the buses and branches of the network are equipped with 2-stage under-voltage and flow violation SPS systems. In each stage, the SPS system will reduce the load on the bus by 10%. The minimum VSM is assumed to be 40%, high and low voltage $\pm 5\%$ and maximum loading of the branches is considered 90%. Fig. 2 represents the modified network. The simulations are conducted using Manpower

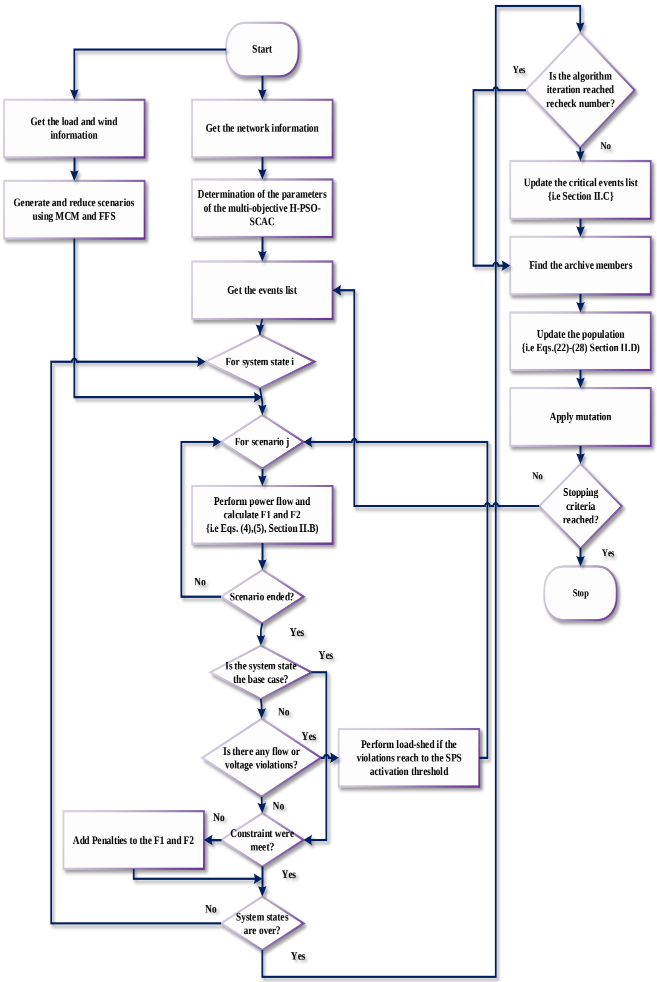

Fig. 1. The flowchart of the proposed method

version 6 software packages. The algorithm was implemented in MATLAB R2017a and executed on a core-i5 laptop with a 2.6 GHz processor and 6.0 GB of RAM. Necessary data for calculating the costs of the generator's active and reactive power, as well as the system data, are available in Appendix B. The PSO population size algorithm is set to 60 and the repository size is set to 25. Maximum iteration is set to 100.

B. Simulation Results

To evaluate the effectiveness of the presented method, three scenarios are investigated as follows:

1- The ORPD considering wind and load uncertainties, expected L-index and EL as F1 and F2.

2- SC-ORPD

3- Proposed RB -ORPD *scenarios*

4- Sensitivity analysis of the method

1. Scenario I: ORPD considering wind and load uncertainties, expected L-index and EL as F1 and F2.

This scenario is simulated to compare the results of the proposed method with those of other literature. Table 3 displays the Pareto front for the proposed method, other references, and the original MOPSO approach. F1 for the

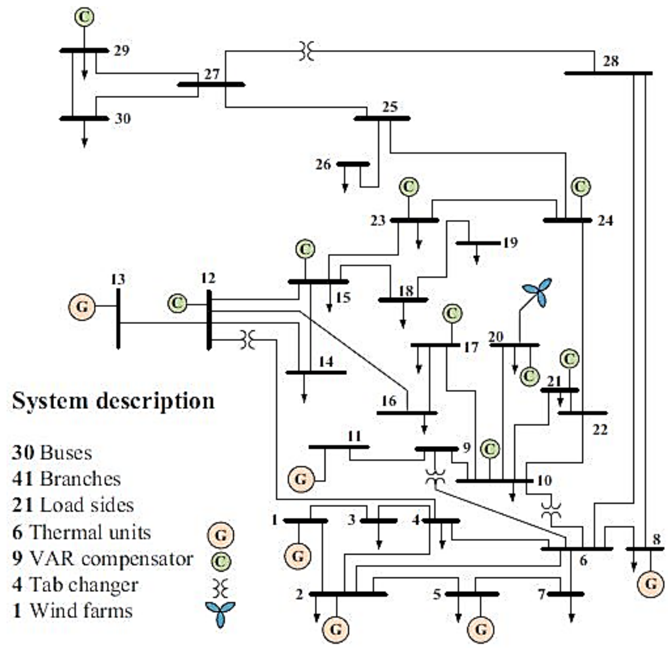

Fig. 2. The single-line diagram of the test system

2. *Scenario II: SC-ORPD*

proposed method ranges from 0.0998 to 0.151, and F2 ranges from 3.23 to 4.09 in the Pareto front. It is evident from the results that the proposed method outperforms other methods in objective minimization, except for reference [11] in the minimization of F1. The results obtained by reference [11] are 6% better in terms of F1 and 13% worse in terms of F2 compared to the proposed method in the objective minimization case. However, the simulation time of the proposed method is 28% of that in [11]. Comparing the obtained results to those of the original MOPSO demonstrates the superiority of the proposed method in terms of objective minimization and solution diversity. Although the simulation time of the proposed method is 56% longer than that of the original MOPSO due to additional calculations.

This scenario is conducted to analyze the impact of security rather than risk-based planning. The L-Index is considered F1, and the economic objective is considered F2. The voltage of the buses and the flow limits are formulated as hard limits. The proposed method for filtering events has been modified to select the most severe contingencies instead of high-risk ones. To investigate the effect of the SPS system, a simulation was conducted under heavy load conditions (load factor = 1.1). Also, two operational strategies with different weighting factors for the sub-objectives are investigated to analyze the effect of the relative importance of each function. The load cut price in Stages 1 and 2 are set at 10 and 20 \$/MW, respectively. The incremental and opportunity cost of the generators is considered to be 10 \$/MW. The initial contingency list contains the following branch numbers: 4, 39, 38, 36, 13, 19, and 14, as well as generator numbers 3, 4, 5, 6, and wind farm outages.

TABLE 3

COMPARING THE RESULTS WITH PUBLISHED REFERENCES

Reference	EL-INDEX	EL (MW)	TIME
Reference [27]	0.1192-0.1317	4.55-7.07	-
Reference [28]	0.111-0.121	4.4-6.6	-
Reference [29]	0.1161-0.1258	3.4815-4.0646	-
Reference [11]	0.0939 -0.17	3.74-4.082	4000
Original MOPSO	0.1101 -0.1208	4.35-4.73	722
Proposed method	0.0998-0.151	3.23-4.09	1127

The results are available in Table 4. By employing the first strategy (using similar weighting factors for the sub-objective functions), F1 varies from 0.79 to 0.799, and F2 varies from 138.2 to 196.63. All solutions involve 4.6 MW of load shedding. In the second strategy, the F1 varies from 0.77 to 0.808 and the F2 varies from 95.5 to 165 dollars.

In this strategy, the load cut of the solutions includes 0, 4.6, and 10.9 MW. The solution with the lowest cost and highest security is related to 0 MW of load shedding. With this selection, the customer's power supply is maintained. In the first strategy, the scheduled VSM is preserved by implementing load cuts for all solutions. However, in the second strategy, some solutions result in minor VSM violations.

By assigning different weighting factors, operators can mitigate the effects of load increases and events on the system and customers. As evident from the results, the operational cost has significantly increased due to the network's heavy load condition and the network's security-focused planning.

3. *Proposed RB-ORPD*

In this scenario, the proposed method based on the flowchart shown in Figure 3 is applied to the test system. The likelihood and consequences of the event are used to calculate the risk of contingencies. The scenario is divided into cases with two weighting factor strategies, similar to the previous scenario. Table 5 shows the results. As is clear from the results, RB-ORPD provides fewer economic objectives compared to Scenario 2. The branches have a lighter load and the bus voltages are at a higher level. Hence, not only does the economic objective decrease, but the security of the system also increases compared to traditional planning.

In strategy 1, load shedding of 0, 4.6, and 12.7 MW is performed in the solutions. While strategy 2 leads to 0, 4.6 MW of the load is shed. In Strategy 2, the emphasis is on utilizing the reactive power of the generators and shunt compensators. So, a reduction in load shedding is implemented, and the economic objective is decreased. So, it can be inferred that risk-based planning, compared to traditional planning, will lead to better and more efficient allocation of resources. The economic objective is achieved and the security of the system is also increased. In addition, the impact of these events on the customers is also reduced.

TABLE 4

THE RESULTS FOR THE SCENARIO II

WEIGHTING FACTORS w21-w22-w23-w24	F1	F2 ($)	MAXIMUM VSI	MAXIMUM LOADING %	MINIMUM VOLTAGE P.U
1-1-1-1	0.79-0.799	138.4-141	0.79	111	0.94
0.2-0.2-0.3-0.3	0.77-0.808	95.5-165	0.77	118	0.91

TABLE 5

THE RESULTS FOR THE SCENARIO III

WEIGHTING FACTORS w21-w22-w23-w24	F1	F2 ($)	MAXIMUM VSI	MAXIMUM LOADING %	MINIMUM VOLTAGE P.U
1-1-1-1	0.01454-0.155	93-153.5	0.7922	1.02	0.973
0.2-0.2-0.3-0.3	0.0148-0.1625	48.34-101	0.7937	1.0234	0.954

4. Sensitivity Analysis

This subsection is dedicated to the sensitivity analysis of the proposed method. First, the sensitivity analysis is done on the MMC method and next the effect of assigning the various important factor to the sub-objective functions is investigated.

4.1 *MMC method sensitivity analysis*

Since using different importance factors of statistical properties leads to various optimal solutions, in this sub-section different importance factors are assigned to examine the sensitivity of the method to these parameters and the robustness of the method. In addition, the sensitivity to the number of statistical properties is also analyzed. Table 6, shows the obtained results. It can be concluded from the obtained results that, the effect of various important factors on the OFV depends on the opinion of decision-makers and planners. The OFV reaches near zero in all cases. However, in the cases where a statistical property is assigned a greater importance factor, the number of estimated outcomes by the algorithm may decrease. In fact, the same scenarios may be estimated. In the case with $\omega_1 = 1$, 10 identical points equal to the mean value will be estimated by the MMC. In addition, if the number of outputs decreases, the OFV will be increased. For the case with 2 outputs, the OFV reaches 0.142 which is unacceptable. Similar results will be achieved if the PDF is replaced with other PDFs like the normal probability distribution function.

4.2 *Various important factors assigned to sub-objective function F2*

Table 7 represents the obtained results for this sub-section. Various important factors are assigned to the sub-objective function of the F2 to investigate their effects on the obtained results. The simulation is done in the heavy load condition.

First, the important factor of the F_{21} is set to zero, and the others 0.33. Therefore, the cost of reactive power provided by the generators is assumed to be free. The results show that compared to the cases in this case, the technical and economic objective is placed between other cases. The solution of the Pareto front has load cuts of 0, 4.6 MW.

In the second case, the important factor of the F_{23} is set to zero and the others are set to 0.33. In this case, there is no charge for the load cut. So, all the solutions of the Pareto front have load shed from 4.6 to 22.27 MW. Compared to other cases in this case minimum F1 and F2 are achieved. Hence, it can be expressed that the F1 (risk functions) are more sensitive to the load in the simulation condition of the network compared to the reactive power generation of the generators.

This means that, in the PV analysis of the network, the operating point of the network may be close to the nose point. Security analysis of the network shows that without performing reactive power optimization, the system may experience instability following contingencies in the heavy load condition. The system side risk is decreased and the customer side is increased instead in this case.

In the third case, the F_{24} is set to zero and the others to 0.33. It means that the system may have the highest active power balance compared to the other cases. The results show that compared to case 1, F1 and F2 have decreased. In addition, compared to case 1, the solution with a zero MW load cut is achievable. Therefore, it can be concluded in the simulated network operating condition, the active power providing may increase system security compared to reactive power.

IV. Conclusions

In this paper, a multi-objective and risk-based optimal reactive power dispatch with a techno-economic objective function is proposed. The problem formulation takes into account the uncertainty of the wind turbine energy and load forecast. The practical limits of conventional and wind generators were modelled to estimate the capability curve of the generators. In addition, special protection systems were modelled in the proposed method. Based on Hybrid-PSO with sine cosine acceleration coefficients (H-PSO-SCAC), the original multi-objective PSO (MOPSO) was modified, and H-MOPSO-SCAC was presented. The obtained results demonstrated that:

1- The proposed H-MOPSO-SCAC provides better solutions in objective minimization and solution diversity compared to the original PSO and previously published methods. In addition, the simulation time of the proposed method is reasonably low compared to the other methods except the original MOPSO.

2- The analysis of the results showed that considering contingencies in the planning stage (SC-ORPF), may increase operational costs. Also, ignoring the contingencies may lead to system instability (as it is clear from comparing Table 3 and Table 4 results that VSM may decrease after the events significantly).

3- Risk-based ORPD led to fewer economic objectives and more security compared to SC-ORPD planning. Using both planning methods, the desired voltage stability margin was achieved. However, less load cut was performed and bus voltages were increased and branch flows were decreased in risk-based planning.

4- In addition, the results revealed that the solutions with the lowest load shed (lowest customer side risk) will lead to the highest system side risk and vice versa. However, the solution that compromises between the customer and system side risk is achievable using the proposed formulation and assigning different weighting factors to the objective functions. The operators can to select the solution with a high loss of load expectation (high customer risk) and lower system risk or vice versa according to the future operation condition or planning strategies.

TABLE 6
THE SENSITIVITY ANALYSIS OF THE MMC METHOD

	IF	N.Out	OFV	IF	N.Out	OFV
ω_1	0.25	10	$1.0 * 10^{-18}$	0.55	10	$1.4 * 10^{-18}$
ω_2	0.25			0.15		
ω_3	0.25			0.15		
ω_4	0.25			0.15		
	IF	N.OUT	OFV	IF	N.OUT	OFV
ω_1	0.15	10	$2.2 * 10^{-21}$	0.15	10	$5.3 * 10^{-17}$
ω_2	0.55			0.15		
ω_3	0.15			0.55		
ω_4	0.15			0.15		
	IF	N.OUT	OFV	IF	N.OUT	OFV
ω_1	0.15	10	$5.7 * 10^{-17}$	0.5	10	$1.6 * 10^{-22}$
ω_2	0.15			0.5		
ω_3	0.15			0		
ω_4	0.55			0		
	IF	N.OUT	OFV	IF	N.OUT	OFV
ω_1	0.5	10	$2.9 * 10^{-17}$	1	10	$1.8 * 10^{-18}$
ω_2	0			0		
ω_3	0.5			0		
ω_4	0			0		
	IF	N.OUT	OFV	IF	N.OUT	OFV
ω_1	0.25	100	$1.1 * 10^{-17}$	0.25	2	0.142
ω_2	0.25			0.25		
ω_3	0.25			0.25		
ω_4	0.25			0.25		

TABLE 7
VARIOUS IMPORTANT FACTORS FOR THE F2

CASE NO	WEIGHTING FACTORS W_{21}-W_{22}-W_{23}-W_{24}	F1	F2 ($)	LOAD CUT (MW)
1	0-0.33-0.33-0.33	0.0146-0.162	43-56	0-4.6
2	0.33-0.33-0-0.33	0.0137-0.152	27.6-31.6	4.6-10.97-22.27
3	0.33-0.33-0.33-0	0.0144-0.153	35-50	0-4.6-10.97

The author's proposal for future research in this field are:

1- A better and more efficient risk function must be introduced to estimate the real risk of the events. Usually, FOR of the network components in the power system is near zero. Hence, the risk associated with power system component failure may be estimated as insignificant. Especially, in high-impact and low-probability event cases.

2- Probable modelling of protection relays can increase the applicability and practicality of the planning.

3- Considering the risk of not realizing the prediction made about the occurrence of random variables in the planning.

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Appendix A

Moment Matching Method

In this paper, the Moment Matching (MMC) method is employed for discretizing continuous PDF of uncertain variables. In this method, an optimization problem must be solved that minimizes the distance between statistical specifications of continuous distributions and statistical properties of fitted discrete distributions subject to a constraint ensuring the summation of the weighting factors to be one. In this study mean, variance, kurtosis, and skewness have been used as statistical specifics.

$$\min \sum_{k\epsilon K} \omega_k (f_k(x,\pi)\text{-}VAL_k)^2$$

s.t.

$$\sum_{v\in\gamma} \pi_v = 1$$

$$\pi_v \leq 0 \; v \in \gamma$$

Where, k is a statistical property, K is a set of all statistical properties, ω_k refers to the importance weight of statistical property k, v is the outputs, x is the vector of realizations for uncertain factors, π Probability vector for outputs, VAL refers to the value of the statistical property of k. We assume the continuous distribution of uncertain factors are independent of each other. The minimum number of outcomes can be achieved by:

$(D+1)y\text{-}1 \sim$ the number of scenarios

Where, D indicates the dimension of the scenario, and y represents the number of outputs. In this paper D is 2 (the product of 2 random variables and 1 period of time). The number of specifications is 8 (the product of 2 uncertain variables, 1 period of time, and 4 moments). Therefore, according to (8), the value of y is 4. To get better results, we chose 5 as the number of scenarios for each random variable.

The nonconvex nonlinear problem was solved by the COUENNE solver in GAMS 23.5. The weighting factors are considered to be equal. The obtained solution with an objective function value of zero or close to zero demonstrates that generated outcomes have statistical properties which perfectly match with specified properties of continuous distributions.

Appendix B

The proposed method is implemented on the modified IEEE-30 bus system. This network has 30 buses, 6 generators (bus 1 as slack bus and 2, 5, 8, 11 and 13 as PV buses), 41 branches (including 4 ULTC transformers at buses 6-9, 6-10, 4-12, 28-27 and non-transformer branches) and 9 compensators (buses 10, 12, 15, 17, 20, 21, 23, 24 and 29). A 60 MW DFIG wind farm is installed at bus 20. The minimum and maximum voltage control range of the ULTCs and the generators are set to 1.1-0.9 P.U. Table A, represents the active and reactive cost data used for the network.

TABLE A
PARAMETERS FOR ACTIVE AND REACTIVE POWER COST

Generator	a_p	b_p	c_p	a_q	b_q	c_q
G_1	0.02	2	0	0.0084	-0.00075	0.2
G_2	0.0175	1.75	0	0.007	0.00322	0.84
G_3	0.0625	1	0	0.0073	-0.00344	0.89
G_4	0.00834	3.25	0	0.0073	-0.00344	0.89
G_5	0.025	3	0	0.0073	-0.00344	0.89

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