Online Static Security Margin Improvement based on Wind Farms

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Received: 2015/10/20 Accepted: 2015/12/5

Abstract

Due to the high penetration of wind farms in the networks, they can have a significant role in the control of power systems. In this paper, wind farms (WFs) are used to improve the static security margins of the power system. Generation rescheduling is one of the remedies to improve the static security margins of the power system. In this paper, the generation rescheduling is presented based on wind farms. To assess the security of the power system, the net active and reactive (generation minus demand) powers of all buses are selected as features. The numbers of the features are reduced based on one of the famous methods of the feature extraction methods named Principle Component Analysis (PCA). The feature extraction method is used to save all features effects on the security of the power system. In this paper, to find the most optimum way to improve the static security margins, two optimization problems are introduced for the two strategies presented. The proposed method is implemented on the IEEE 39-bus network and the results show its effectiveness on the static security margin. It should be mentioned that the proposed method can deal with correlated random variables. Nataf transformation is used to build more accurate and more realistic database to train the classifier to assess the static security margins of the power system. The real data of Iran's grid are used to validate the Nataf transformation.

Keywords: Static Security Assessment, Decision Tree, Preventive Control, Wind Farms.

Notation

The main notation used in this paper is stated below, while other symbols are defined as needed.

Constants

B_k	Susceptance of line *k*
$f_k^{\max}$	Transmission capacity of line *k*
$FV_{n,f}$	Feature vector (step 4 of PCA algorithm)
ME_n	Mean value of each feature (step 1 of PCA algorithm)
MIN_f^a	Lower limit of f^{th} feature in a^{th} area
MAX_f^a	Upper limit of f^{th} feature in a^{th} area
$MIN_f^{s_a}$	Lower limit of f^{th} feature in s_a^{th} secure area
$MAX_f^{s_a}$	Upper limit of f^{th} feature in s_a^{th} secure area
$\overline{P_i^G}$	Upper limit of the i^{th} generation unit
$\overline{\overline{P_i^G}}$	Power scheduled to be produced by the i^{th} generation unit before the generation rescheduling
$\overline{P_l^W}$	Maximum output power of l^{th} wind farm
$\overline{\overline{P_l^W}}$	Output power of l^{th} wind farms before the generation rescheduling
l_i^G	Marginal Cost of i^{th} generation unit

Variables

f_k	Power flow through line *k*
F_f	Amount of f^{th} feature
F_f^z	Amount of f^{th} feature in z^{th} scenario
P_i^G	Power scheduled to be produced by the i^{th} generation unit
P_l^W	Output power of l^{th} wind farm
d_n	Voltage angle at bus *n*

Indices

a	Indices of areas in feature space
f	Indices of features
i	Indices of generators
j	Indices of loads
k	Indices of lines
l	Indices of wind farm
n	Indices of buses
r(k)	Receiving-end bus of line *k*
s(k)	Sending-end bus of line *k*
s_a	Indices of secure areas in feature space
t	Indices of types of agreements

Sets

Ω^{A_s}	Set of indices of secure areas
Ω^D	Set of indices of demands
Ω^F	Set of indices of features
Ω^G	Set of indices of generation units
Ω^K	Set of indices of lines
Ω^N	Set of indices of buses
Ω^N	Set of features which control and classify the security
Ω^M	Set of features which classify the security
Ω^W	Set of wind farms
y_n^G	Set of indices of generation units located at bus *n*

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y_n^D Set of indices of demands located at bus n

y_n^W Set of indices of wind farms located at bus n

I. Introduction

The security assessment of a power system refers to the problem of how well a particular system condition can withstand some credible contingencies. Modern power systems are being pushed to operate near their security limits by the growing load demand and inadequate infrastructure investments in many networks. On the other hand, the deregulation of electric utilities and large amount of penetration of renewable energy has introduced increasing uncertainties and complexities to the systems. As security is a major goal of power system operation and control, a fast and reliable security assessment is necessary. The security is an important issue for utility engineers and researchers [1-14]. Some researchers have used numerical methods to assess the security of the power system. In numerical methods [2-4], a non-heuristic method is used. On the other hand, some researchers have used machine learning methods and different classifiers to assess the security of the power system [5-14]. In machine learning based methods, a database is built, and then the database is used to train a classifier. Different feature selection and feature extraction [12] algorithms have been applied to machine learning based methods. In these methods, independent random variables have been used to build the database, but in real networks, there is a correlation between the generations and loads, i.e., in peak hours almost all the buses have their peak consumption. In this paper, a new method is used to overcome this problem.

High penetration of distributed energy resources in networks encourages the operators to use them to control the states of the power system. Among renewable energy resources, wind energy is used well and has a major role in providing electrical energy all over the world. One of the main issues in power systems is the security of the network.

Improving the security margin of the power system is an interesting subject in the literature. Different methods have been proposed on this subject [15, 16, 20, 22 and 23].

The difference among these methods lies in selecting a strategy for generator selection and selecting the loads to be shed. In [22] the feature selection method has been used to select the most effective loads. The sensitivity of each generator to the transient stability index has been calculated. Based on this sensitivity, the most effective generator to change the transient stability index is selected. The most effective generators are participated in the generation rescheduling program. In [22-23] a feature selection method has been used to choose the most effective generators. In [22] the selection of loads is based on the proposed sensitivity calculations. The sensitivity calculations are based on critical interface power flow with respect to changes in the load. In [18], the security constraint Optimal Power Flow (OPF) has been proposed. In [18], DT is used to build a constraint for the security constraint OPF. In [18] the RELIEF algorithm is used to select the most effective generators. In [19], the same work is carried out as compared to [18], but the pattern discovery method has been used to add some constraints to the OPF.

The maintenance cost of conventional generators increases when the oscillations of output power of generators increase, and also the lifetime of generators decreases. Using green energy resources to control the states of the power system becomes more interesting for system operators. In this paper, the wind farms are used to improve the security of the power system. The output of WFs is set to the highest possible value. Thus, the output of WFs can only decrease. To decrease the output power of the WFs, some wind turbines fall out or the converter set points are changed.

The novelties and contribution of this paper are as follows:

- The wind farms are used to improve the static security margin of the power system,
- The Nataf transformation is used to generate more accurate random data, and
- The security constraint is presented as a linear relation in the optimization problem

This paper is organized as follows. In section II, the proposed method is introduced. In section III, Simulation results and the case study are presented and finally the conclusion of the paper is presented in section IV. Nataf transformation and Principal Components Analysis (PCA) are explained in appendix section.

II. Proposed Method

The proposed algorithm is divided into 5 steps. These steps are introduced as follows.

Step 1: Database Generation: The first step of this algorithm is to assess the static security of the power system. In this paper, the machine learning method is used to assess the static security of the power system. The first step in machine learning based methods is to build the proper database. The database is built based on time consuming off line simulations. Different scenarios with different load levels are simulated. Different load levels are generated based on random generation numbers. The probabilistic distribution functions of the loads are assumed to be known.

In [3-14] random variables, loads and generation of different buses have been built for different scenarios. In these papers, no correlations among the

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variables have been considered. In a real network, there is a correlation among different loads and generations. In addition to loads and generations, the adjacent wind farms have correlated outputs, too. In the proposed method, the correlations between variables are modeled with Nataf transformation. This transformation is introduced in appendix.

Based on the Nataf transformation, different load levels are generated. The amounts of generations are calculated based on optimal power flow equations.

Step 2: Feature Extraction: Different features have been used in the literature to assess the static security of the power system. In this paper, the net active and reactive power of each bus is used to assess the static security of the power system. The numbers of buses in the real networks are very high; therefore, the numbers of the features should be decreased. Different feature selection and feature extraction methods have been used in different studies. In this paper, one of the famous methods of feature extraction named Principal Component Analysis (PCA) is used. PCA is introduced in appendix. In feature extraction methods all the features have an effect on each extracted features. The PCA is modeled based on simple summations and multiplications, and these equations are linear so they can be used in the main MILP problem.

The numbers of final features are selected based on sensitivity analysis. The error of classification errors is calculated based on different numbers of features, and the best candidate is chosen.

As it is mentioned, the net active and reactive power of all buses are selected as features in this paper. The selected features are reduced by PCA. The net active power of WFs are separated and the other features are reduced by PCA. The final number of input features is $N+M$, in which N is the number of WFs, and M is the reduced number of features, as it is shown in Fig-1.

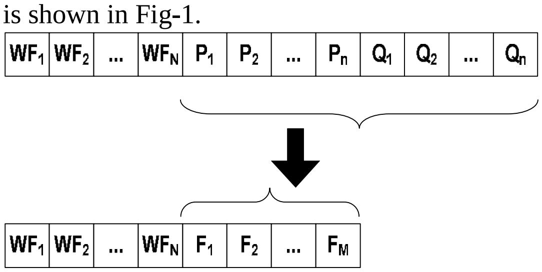

Fig-1: Number of Features in the Proposed Problem

As it is shown in Fig-1, N is the number of the wind farms in the network and n is the number of buses. M is the number of reduced features by PCA.

Step 3: Assess the Static Security Status: Among different classifiers, the decision tree (DT) is selected. The DT divides the feature spaces to separate subspaces, with some simple if-then rules. These if-then rules can model with linear equations. The main problem of this paper is written in a mixed integer linear programming (MILP) form; therefore, the decision tree is selected.

The DT is trained by the extracted features of the database, and divides the feature to subspaces. Some of the subspaces are "secure" parts and the others are "insecure". The trained DT classifies the security state of the power system.

Step 4: Static Security Margin Improvement (Strategy 1): As it is mentioned before, each scenario is classified as secure or insecure. Each insecure case should be converted to the secure case with some preventive actions. Generation rescheduling is one of the methods which is used as tools to improve the static security margin of the power system. In this paper, wind farms are used to improve the static security margin. Due to the high penetration of renewable energy resources, they can also be used for system security improvement.

In generation rescheduling methods, conventional generators are used. In normal situations the output of the generators are calculated based on optimal power flow calculations. In insecure cases, the outputs of the generators are changed based on the generation rescheduling commands.

In this paper, the wind farms have been used to control the security of the power system. The renewable energy resources have been used as a substitute of conventional generators because of [26]:

- The maintenance cost of conventional generators increases when the output powers of generators change.
- The high penetration of renewable energy resources makes the operator of the power system use them for security purposes.

The system operator uses the renewable energy resources as much as possible. So the outputs of the distributed energy resources are in the maximum available energy at all times. So, the operators that improve the security margins can only reduce their outputs. The reduced energy must compensate with other resources. In this paper, an optimization problem is solved to find the cheapest way to compensate this reduction in energy.

As it is mentioned, the outputs of the DT are if-then rules. These rules divide the feature spaces to different parts. Each part represents a unique class. In this paper, there are two classes, secure and insecure classes.

The proposed algorithm is introduced through an example. Consider a problem with two input features named '*X1*' and '*X2*' and two output classes named '*A*' and '*B*'. Suppose that DT classifies the feature spaces with the rules which are shown in Fig-2.

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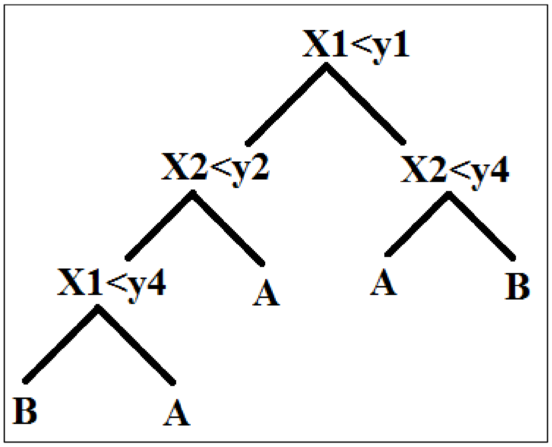

Fig-2: DT for Typical Case

The feature spaces with two dimensions are divided into 5 areas as shown in Fig-3. The dotted areas are labeled as class ‘A’ and the shaded areas are labeled as class ‘B’.

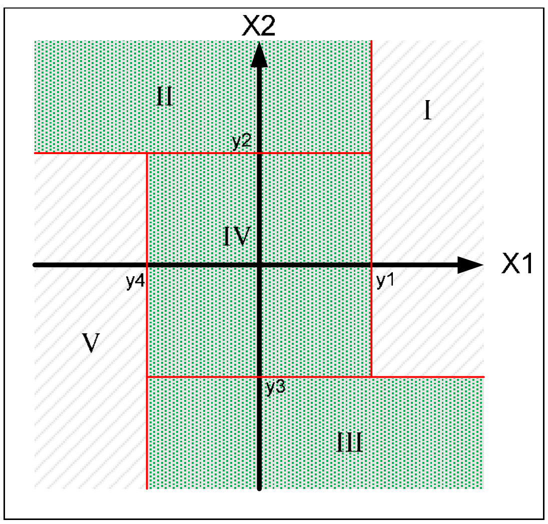

Fig-3: Feature Spaces for Typical Case

The margins of these areas are presented in Table-I.

Table-I: The Margins of Areas for Typical Case

Area	Feature X1		Feature X2	
	lower Bound	Upper Bound	lower Bound	Upper Bound
Area 1	**y1**	+∞	**y3**	+∞
Area 2	-∞	**y1**	**y2**	+∞
Area 3	**y4**	+∞	-∞	**y3**
Area 4	**y4**	**y1**	**y3**	**y2**
Area 5	-∞	**y4**	-∞	**y2**

The same method is used for $N+M$ dimensional feature spaces and each area is presented with the same constraints as the constraints of Table-I. As it is mentioned, the DT divides the feature space to some secure and insecure areas and for each area in $N+M$ dimensional feature space there are constraints as (1).

$$MIN_f^a < F_f < MAX_f^a \ ,\forall f \in \Omega^U \tag{1a}$$

$$MIN_f^a < F_f < MAX_f^a \ ,\forall f \in \Omega^V \tag{1b}$$

In strategy 1, for each insecure scenario z, the proposed method seeks for the secure areas (s_a) which satisfy the constraints (2):

$$MIN_f^{s_a} < F_f^z \ ,\forall f \in \Omega^U ,\exists s_a \in \Omega^{A_s} \tag{2a}$$

$$MIN_f^{s_a} < F_f^z < MAX_f^{s_a} \ ,\forall f \in \Omega^V ,\exists s_a \in \Omega^{A_s} \tag{2b}$$

If there is any secure area (s_a), then strategy 1 would be implemented. In strategy 1, the first N features are the output active power of wind farms. As it is mentioned before, the wind farms can only reduce their production. Therefore, the output active power of wind farms must be greater than the $MIN_f^{s_a}$. The wind farms production can be greater than $MAX_f^{s_a}$ or less than it. Since the production of wind farms can only reduce, the output active power of wind farms will be calculated based on (3).

$$\overline{P_l^W} = \min\left\{ \overline{\overline{P_l^W}}, MAX_l^{s_a} \right\}, \ \forall l \in \Omega^W \tag{3}$$

The output active power of some wind farms is reduced and the total reduced active power of wind farms will compensate by conventional generators. The changes in the generators are selected based on the following optimization problem.

The objective function can be formulated using the following model:

Minimize Δ^{WF}

$$\sum_{i \in \Omega^G} l_i^G P_i^G \tag{4a}$$

Subject to

$$MIN_l^{s_a} \le P_l^{WF} \le \overline{P_l^{WF}} \tag{4b}$$

$$F_{f,s}^{\min} \le \sum_{n \in \Omega^N} \left(\begin{bmatrix} \sum_{i \in y_n^G} P_i^G - \sum_{j \in y_n^D} P_j^D \\ + \sum_{l \in y_n^W} P_l^W - ME_n \end{bmatrix} \times FV_{n,f} \right) \le F_{f,s}^{\max} \tag{4c}$$

$$, \ \forall f \in \Omega^F ,\exists s_a \in \Omega^{A_s}$$

$$\sum_{i \in y_n^G} P_i^G - \sum_{k|s(k)=n} f_k + \sum_{k|r(k)=n} f_k - \sum_{j \in y_n^D} P_j^D + \sum_{l \in y_n^W} P_l^W = 0, \forall n \in \Omega^N \tag{4d}$$

$$f_k = B_k (d_s(k) - d_r(k)), \ \forall k \in \Omega^K \tag{4e}$$

$$-f_k^{\max} \le f_k \le f_k^{\max}, \ \forall k \in \Omega^K \tag{4f}$$

$$0 \le P_i^G \le \overline{P_i^G}, \ i : ref \tag{4g}$$

$$P_i^G = \overline{\overline{P_i^G}}, \ \forall i \in \Omega^G \setminus i : ref \tag{4h}$$

$$-p \le d_n \le p, \ \forall n \in \Omega^N \setminus n : ref \tag{4i}$$

$$d_n = 0, \ n : ref \tag{4j}$$

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The objective function (4a) of the problem is the cost of generators. Constraint (4b) limits the output active power of wind farms. The lower bound of (4b) limits the lower bound of the secure area (s_a). The upper bound of (4b) limits (3).

Constraint (4d) imposes the KCL law in each bus of the system. Constraint (4e) calculates the power flow through each line which is limited by constraint (4f). Constraint (4g) imposes the generation limits of slack bus. Constraint (4h) fixed the generation of other generation units due to one of the main objectives of this paper, which is the reduction of wear and tear cost of conventional generators by the reduction of oscillation of the generators output. Constraint (4i) bounds the voltage angles, and finally, equation (4j) fixes the voltage angle of the slack bus to zero.

Constraint (4c) is a security constraint. The security constraint has been presented as a nonlinear constraint of the optimization problem in the literature[31]. To eliminate this non linearity and solve the problem much faster, in this paper, the security constraint is presented as a linear equation using the decision tree. As mentioned, the decision tree (DT) is used to assess the security of the power system. The DT splits the feature space into the subspaces labeled as “Secure Area”, and “Insecure Area”. The margins of the secure areas are used as the security constraint.

For each insecure scenario, the margins of the secure areas which satisfy (2) are selected. The optimization problem is repeated for the number of selected secure areas.

The optimization variables of problem (4) are the variables in the set $\Delta^{WF}=\{P_i^G,\ i: ref\ ; f_k, \forall k \in \Omega^K\ ; \delta_n\ , \ \forall n \in \Omega^N\ ;\ P_l^w\ ,\ \forall l \in \Omega^W\ ;\ P_j^t\ ,\ \forall j \in \Omega^D, \forall t \in \Omega^T\ \}$.

<u>Step 5: Checking the Availability of the First Strategy (Strategy 2):</u> In some insecure cases, there is not any feasible solution for the optimization problem, i.e. reduction of the WFs production cannot properly improve the security margin. In these cases, conventional generators are used for generation rescheduling purposes. One optimization problem is solved to find the best way to improve the static security margins of the power system. The optimization problem's objective function and its constraints are introduced as follows:

The objective function can be formulated using the following model:

Minimize Δ^{GR}

$$\sum_{i \in \Omega^G} l_i^G P_i^G \tag{5a}$$

Subject to

$$\sum_{i \in y_n^G} P_i^G - \sum_{k|s(k)=n} f_k + \sum_{k|r(k)=n} f_k - \sum_{j \in y_n^D} P_j^D + \sum_{l \in y_n^W} P_l^W = 0, \forall n \in \Omega^N \tag{5b}$$

$$f_k = B_k(d_s(k) - d_r(k)),\ \forall k \in \Omega^K \tag{5c}$$

$$-f_k^{\max} \le f_k \le f_k^{\max},\ \forall k \in \Omega^K \tag{5d}$$

$$0 \le P_i^G \le \overline{P_i^G},\ \forall i \in \Omega^G \tag{5e}$$

$$-p \le d_n \le p,\ \forall n \in \Omega^N \setminus n: ref \tag{5f}$$

$$d_n = 0,\ n: ref \tag{5g}$$

$$F_{f,s}^{\min} \le \sum_{n \in \Omega^N} \left(\begin{bmatrix} \sum_{i \in y_n^G} P_i^G - \sum_{j \in y_n^D} P_j^D \\ + \sum_{l \in y_n^W} P_l^W - ME_n \end{bmatrix} \times FV_{n,f} \right) \le F_{f,s}^{\max}\ ,\ \forall f \in \Omega^F, \exists s \in \Omega^S \tag{5h}$$

$$P_l^W = \overline{\overline{P_l^W}},\ \forall l \in \Omega^W \tag{5i}$$

The objective function (5a) of the problem is the security constraint DC-OPF.

Constraint (5b) imposes the KCL law in each bus of the system. Constraint (5c) calculates the power flow through each line which is limited by constraint (5d). Constraint (5e) imposes the generation limits of generation units. Constraint (5f) bounds the voltage angles, and finally, equation (5g) fixes the voltage angle of the slack bus to zero.

Constraint (5h) is the security constraint. Constraint (5i) fixed the production of wind farms on the amount of the production before generation rescheduling. The optimization variables of problem (5) are the variables in the set $\Delta^{GR}=\{P_i^G,\ \forall i \in \Omega^G\ ; f_k, \forall k \in \Omega^K\ ; \delta_n, \forall n \in \Omega^N\ \}$.

The flowchart of the proposed method is shown in Fig-4.

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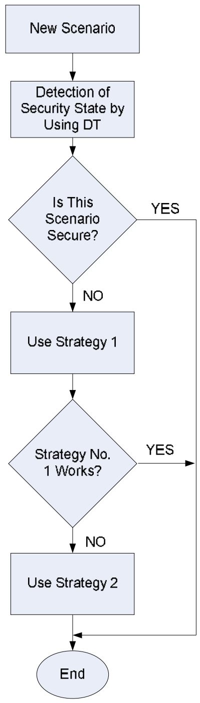

Fig-4: Flowchart of Proposed Method

III. Case Study

The proposed method is implemented on the IEEE 39-bus network. The five steps of the problem are introduced in this section.

Step 1: Database Generation: The Nataf transformation is used to generate the correlated data. The PDF of loads is presented in Table-I.

Table-I: Probabilistic Distribution Function of Loads

Type	Load PDF	No. of Buses
1	Gaussian	1-2-3-4-5-8-10-12-13-14-15-16-21-25
2	Discrete	18-26
3	Uniform	4-23-29

The loads of some buses are correlated together. The CCM of the loads which are located at buses 15, 16 and 21, is as follows:

$$\begin{array}{c c} & \begin{array}{ccc} 15 & 16 & 21 \end{array} \\ \begin{array}{c} 15 \\ 16 \\ 21 \end{array} & \begin{bmatrix} 1 & 0.2 & 0.3 \\ 0.2 & 1 & 0.4 \\ 0.3 & 0.4 & 1 \end{bmatrix} \end{array} \tag{6}$$

The CCM of the loads, which are located at buses 4 and 29 and have uniform PDF is as follows:

$$\begin{array}{c c} & \begin{array}{cc} 4 & 29 \end{array} \\ \begin{array}{c} 4 \\ 29 \end{array} & \begin{bmatrix} 1 & 0.4 \\ 0.4 & 1 \end{bmatrix} \end{array} \tag{7}$$

The CCM of the loads which are located at buses 25 and 23, is as follows:

$$\begin{array}{c c} & \begin{array}{cc} 23 & 25 \end{array} \\ \begin{array}{c} 23 \\ 25 \end{array} & \begin{bmatrix} 1 & 0.3 \\ 0.3 & 1 \end{bmatrix} \end{array} \tag{8}$$

The first one has the Gaussian PDF and the latter one has a uniform PDF. In this network it has been assumed that two WFs have been installed on buses 30 and 37. It is assumed that the locations of the WFs are near each other geographically. So, the output powers of these WFs are correlated to each ‘other. The CCM of these WFs is assumed to be as follows:

$$\begin{array}{c c} & \begin{array}{cc} 30 & 37 \end{array} \\ \begin{array}{c} 30 \\ 37 \end{array} & \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix} \end{array} \tag{9}$$

The correlation coefficients mentioned above are considered to build the database to train the DT. The number of generated scenarios and the number of secure and insecure cases are presented in Table-II.

Table-II: Number of Scenarios

Scenario	**Secure case**	**Insecure Case**
9546	3322	6224

As it is mentioned in step 1 of section 2, Nataf transformation is used to create a more real and accurate database. To verify this reality and accuracy, one real case study is simulated in this paper. The active power consumption of five real load buses in Iran’s grid is considered. The mean and standard deviation of these loads are shown in Table-III. The loads have a normal probabilistic distribution function. Based on the known mean and standard deviation and normal PDF, two databases are created. One database is created based on the Nataf transformation and the other is created based on normal random generation numbers. The mean and standard deviation of these two created databases are presented.

As it is shown in Table-III, the mean value and standard deviation of two generated databases are close to the real database, but the real active power consumptions have a correlation between each other. The correlation coefficients between the real database and the two generated databases are shown in (10).

$$\begin{bmatrix} 1 & 0.8377 & 0.7149 & 0.7052 & 0.7812 \\ 0.8377 & 1 & 0.7413 & 0.7523 & 0.8610 \\ 0.7149 & 0.7413 & 1 & 0.9552 & 0.9503 \\ 0.7052 & 0.7523 & 0.9552 & 1 & 0.9517 \\ 0.7812 & 0.8610 & 0.9503 & 0.9517 & 1 \end{bmatrix} \text{(10a)}$$

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$$\begin{bmatrix} 1 & 0.8399 & 0.6905 & 0.6859 & 0.7650 \\ 0.8399 & 1 & 0.7413 & 0.7502 & 0.8622 \\ 0.6905 & 0.7413 & 1 & 0.9533 & 0.9463 \\ 0.6859 & 0.7502 & 0.9533 & 1 & 0.9482 \\ 0.7650 & 0.8622 & 0.9463 & 0.9482 & 1 \end{bmatrix} \quad (10b)$$

$$\begin{bmatrix} 1 & -0.0558 & 0.0452 & -0.0306 & -0.0196 \\ -0.0558 & 1 & -0.0011 & 0.0201 & -0.0364 \\ 0.0452 & -0.0011 & 1 & 0.0587 & -0.0614 \\ -0.0306 & 0.0201 & 0.0587 & 1 & -0.0176 \\ -0.0196 & -0.0364 & -0.0614 & -0.0176 & 1 \end{bmatrix} \quad (10c)$$

Table-III: Mean and Standard Deviation of Active Power Consumption for Real Load Buses

	Real Data		**Nataf Based Database**		**Normal Database**	
Load Bus Name	Mean Value (MW)	Standard Deviation (MW)	Mean Value (MW)	Standard Deviation (MW)	Mean Value (MW)	Standard Deviation (MW)
Tehran	6164.31	873.51	6173.512	845.303	6147.305	821.646
Mazandaran	1667.28	407.32	1675.343	406.4808	1686.251	406.5551
Isfahan	791.84	191.19	793.565	189.8465	794.9269	194.3038
Kerman	1299.19	251.63	1303.474	250.071	1296.753	781.937
Fars	2586.77	787.59	2600.233	251.0426	2657.964	777.6739

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The Correlation coefficient matrix (CCM) of (10a) is for real data, (10b) is for the Nataf based database and (10c) is for the normal based database. As it is obvious the CCM of the Nataf based database is very similar to the CCM of the real database. The CCM of the normal random generation is very far from the real CCM. This comparison shows the accuracy of the Nataf transformation and shows that the Nataf based database is closer to reality than the normal database.

Step 2: Feature Extraction: The test case has 39 buses, so it has 78 net injected active and reactive powers as the selected features. Among these features, the net injected active power of WF buses 30 and 37 are eliminated, and 76 features are reduced to 10 features using the PCA method. These 10 features, in addition to the 2 net injected active powers of buses 30 and 37; become 12 features which are used to train the DT and control the security margin of the power system.

Step 3: Assess the Static Security Status: The inputs of the DT are twelve extracted features and the output of the classifier is the static security status of the power system. The output has two classes named 'Secure' and 'Insecure'. The resubstitution error and k-fold cross validation error [27] of the classification are presented in Table-IV. As it is mentioned in step 1, the Nataf transformation is used to generate more realistic random numbers. The classification errors of the decision tree in two cases are presented in Table-IV. In case 1, the random numbers are generated separately and are between 50-200 percent of their base values [3], but in case 2, the random numbers are generated based on Nataf Transformation. Through the results, it is shown that the classification based on Nataf transformation has better performance.

Table-IV: The Resubstitution and k-fold Cross Validation Error of Classification in Two Cases

Case	Resubstitution Error (%)	k-fold Cross Validation Error (%)
Case 1 (Normal)	2.8	13.11
Case 2 (Nataf)	0.4	3.26

Step 4: Static Security Margin Improvement (Strategy 1): To show the implementations of this step, one of the scenarios is selected as an example. As it was mentioned before, for each insecure case, some secure areas have been found which satisfy (2). For example, one of the insecure cases has the following features:

$$\begin{aligned}
&F_1 = 207.98, && F_2 = 447.95 \\
&F_3 = -6.97, && F_4 = -363.34 \\
&F_5 = -115.71, && F_6 = -231.89 \\
&F_7 = 342.89, && F_8 = -19.50 \\
&F_9 = 0.436, && F_{10} = 0.243 \\
&F_{11} = 1.372, && F_{12} = 39.79
\end{aligned} \tag{11}$$

As it is mentioned, the net active and reactive powers of the buses are selected as the features to assess the static security of the power system. In this paper, the PCA algorithm is used to reduce the number of features. As mentioned, the final number of features is N+M, in which N is equal to the number of wind farms that have participated in the generation rescheduling program. In this paper, the IEEE 39-bus is selected as a test case. It is assumed that in this network, there are two wind farms both of which have participated in the generation rescheduling program. So, in this test case, N is equal to 2, and the first and second features are the output active power of wind farms on a random case. The remaining 37 buses have 37 active and 37 reactive net powers. These features are reduced to 10 features based on PCA. The three to twelve numbers are the 10 features that are produced by the PCA algorithm based on the 37*2 remaining powers.

In this case, six secure areas are found, in which features three to twelve have been located between margins and features one and two are out of the margins of the secure parts. Therefore, the optimization problem is repeated six times to find the best solution. If all the problems have feasible solutions, the solution with minimum cost is selected to be implemented.

Based on the results of the optimization problem's solutions, the results of the following secure area have the least cost.

$$\begin{aligned}
&186.13 < F_1 < 203.19, \qquad 442.63 < F_2 \\
&F_3 < 1.77, \qquad F_{10} < 12.42 \\
&-9.75*10^4 < F_8 < 5.25*10^4
\end{aligned} \tag{12}$$

The generations of generators between and after the control action are presented in Table-V.

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Table-V: Production of Generators Before and After Generation Rescheduling Program

Bus No.	Before Control Action	After Control Action
31	587.09	587.09
32	586.92	586.92
33	521.12	525.09
34	507.99	507.99
35	523.93	523.93
36	520.95	520.95
38	651.20	651.20
39	679.59	679.59
WF1: 30	207.98	202.19
WF2: 37	447.95	447.95

As it is shown in Table-V, the insecure state is converted to secure state, with only 3.97 MW changes in the generation of the conventional generators.

Step 5: Checking the Availability of the First Strategy (Strategy 2): Among 6224 insecure cases in the generated database, 5333 insecure cases convert to secure state with strategy No. 1. The remaining insecure cases should be improving their static security margins by strategy No. 2.

To compare the ability of the first strategy in contrast to the second strategy, it is assumed that the active power bidding of the 8 generators of the test case are 2, 2.2, 2.4, 2.6, 2.8, 3, 3.2 and 3.4. Based on these prices, the cost of the generation rescheduling program for insecure cases are calculated. In strategy 1, the generation of some generators are changed. The cost of the generation rescheduling program in strategy 1 is equal to the additional cost, which are payed to the selected generators for which the output are changed. In strategy 2, the program cost is equal to the differences of the OPF cost and new generation scheduling cost. The mean and standard deviations of costs of these two strategies are presented in Table-VI.

Table-VI: Mean and Standard Deviations of Two Proposed Strategy Costs

Strategy	Mean (\$/kWh)	Standard Deviation (\$/kWh)
Strategy 1	102.17	51.65
Strategy 2	481.21	58.90

As it is presented in Table-VI, the proposed method can improve the static security margin of the power system with less cost in comparison to the conventional generation rescheduling program [18-19].

IV. Conclusion

In this paper, the Nataf Transformation coupled with Principal Component Analysis technique has been proposed as a means for building a more realistic database and more effective features for power system security assessment.

A new strategy to improve the security margin of the power system has been presented. In the proposed strategy WFs have been used in the generation rescheduling strategy, to improve the security margin. In this strategy, the oscillation of output power of the conventional generator decreases while the maintenance cost of the generators decreases, so the lifetime of generators increases. On the other hand, renewable energy resources are used to improve the security margin of the power system. In each insecure case, two optimization problems have been solved to find the cheapest way to improve the security margin. The second optimization problem is a backup strategy for the first optimization problem. The first optimization problem is based on wind farms and the second one is based on the conventional generators. The linear decision tree based security constraint has been considered in the presented optimization problem. From the results, it is observed that the proposed algorithm can be implemented in real-time applications.

The proposed method has been applied to IEEE New England 39-Bus test case. The simulation results show the effectiveness of the proposed method.

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Appendix

A. Nataf Transformation

Nataf transformation is a mathematical model for the transformation from correlated original space to mutually independent standard normal one [25]. It requires the marginal Cumulative Distribution Function (CDF) of each random variable and their Correlation Coefficient Matrix (CCM), which are easy to be obtained in engineering applications. When the marginal CDF and the CCM of correlated data are available, a correlated Standard Normal Variable (SNV) vector can be obtained by marginal transformation.

The relationship between correlation coefficient of real data r'_{ij} and SNV r_{ij} data can be obtained as follows [25]:

$$r'_{ij} = r_{ij} * F \tag{6}$$

In [25] for each CDF of real data the coefficient of F has been introduced.

The CCM of SNV data can be decomposed by Cholesky decomposition. The inferior triangular matrix of resulting matrix has been used to transform correlated SNV vector to independent standard normal variables. The inverse procedure of mentioned procedure, transform the independent standard normal variables to dependent variables with arbitrary CDF.

B. Principal Components Analysis (PCA)

The PCA is a tool to identifying patterns in data, and express them in such a way as to highlight their similarities and differences [26]. Since patterns in data can be hard to find in high dimension data, PCA is a powerful tool for analyzing the data.

This method has five steps.

Step 1: subtract the mean. In this step, each of the data dimensions is subtracted from mean value of that dimension. This step produces a data set whose mean is zero.

Step 2: calculate the covariance matrix. In this step the covariance matrix of data is calculated. If the data set has N dimensions, then the covariance matrix has the size of $N*N$.

Step 3: Calculate the eigenvectors and eigenvalues of covariance matrix. Since the covariance matrix is a square matrix, the eigenvector and eigenvalues of this matrix can be calculated.

Step 4: Choosing components and forming a feature vector. The data compression has been done. The eigenvector with the highest eigenvalue is the principle component of data set. In this step, at first sort of the eigenvectors should be sorted in descending order, then the first M eigenvectors have been chosen. The selected M features formed the feature vector.

Step 5: Deriving the new data set. In this step the feature vector is multiplied on the left of the original data set. Now, the new data set with M dimensions has been built.

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