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Using integrated method to rank the power system contingency

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Abstract. Contingency ranking is one of the most important stages in the analysis of power system security. In this paper, an integrated algorithm has been proposed to address this issue. This algorithm employs neural networks method to quickly estimate the power system parameters and Stochastic Frontier Analysis (SFA) in order to calculate the efficiency of each contingency. Network security indices (voltage violation and line flow violation) and economic indices (locational marginal price and congestion cost) have been simultaneously considered to rank the contingencies. The efficiency of each contingency shows its severity, and indicates that it affects network security and economic indices concurrently. The proposed algorithm has been tested on IEEE 14-bus and 30-bus test power systems. Simulation results show the high efficiency of the algorithm. Test results indicate that predicted quantities are estimated accurately and quickly. The proposed method is capable of producing fast and accurate network security and economic indices, so that it can be used for online ranking.

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1. Introduction

Investigation of security and contingency analysis in power system is one of the most important tasks of engineers of large power systems. The main task of security analysis is to find critical contingencies and ranking them according to their severity. The result of contingency analysis can be used to save the power system by preventing other cascade accidents [1]. Various methods have been developed for estimating the severity of contingency. In [2], a new composite sensitivity analysis framework has been proposed for voltage contingency evaluation and ranking. The proposed formulation considers the voltage stability margin/instability depth of the entire power system as the severity index for voltage contingencies. The proposed method has been tested on the New Zealand test system and Iran's transmission network. Obtained results have indicated that the proposed method can highly reduce the computation time. In [3], a method capable of selecting contingencies leading to voltage insecurities has been proposed. The contingencies are ordered according to their effects on the system operating state. In [4], a new power sensitivity ranking algorithm for voltage collapse contingency ranking has been proposed. This new ranking algorithm considers

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the future variations in generation dispatch and the short-term load demand forecast. In [5], a fast and precise contingency ranking method for the power systems security analysis has been presented. The method proposed in [5], considers both the apparent power overloading and voltage violations, simultaneously. In [6], a method as a combinatorial optimization problem and solved by genetic algorithms has been proposed to efficiently perform the selection of multiple contingencies. In [7], a contingency assessment method has been proposed that takes into account the nature of probability distribution of power system operating conditions to get realistic severity and risk estimations of contingencies. The developed contingency assessment methods have been applied to SEO region of French EHV system to estimate severities and rank the selected contingencies based on risk of voltage collapse. In [8], an alternative methodology has been proposed for static contingency analyses that only used continuation methods, and thus provided an accurate determination of the loading margin. The applicability and effectiveness of the proposed methodology has been investigated on IEEE test systems (14, 57, and 118 buses) and compared with the continuation power flow.

In recent years, fuzzy system applications and artificial intelligence methodology have received increasing attentions in various areas of power systems. In [1], a novel approach has been proposed for contingency ranking based on static security assessment. The proposed method has been applied to IEEE 30-bus power system, and different cases have been examined. In [9], a hybrid fuzzy-neural network has been developed for ranking of critical contingency using pre-fault load information at selected buses. A multi-output fuzzy-neural network has also been used for contingency ranking. The membership values of the loads have been categorized in lingual groups of low, middle, and high and considered as the input for neural network. A Fuzzy Composite Performance Index (FCPI), formulated by combining voltage violations, line flow violations, and voltage stability margin, has been proposed for composite ranking of contingencies. The performance of the proposed method has been tested on a 69-bus practical Indian power system. In [10], an approach based on radial basis function neural network has been developed to estimate bus voltage magnitudes and angles for normal operation as well as for all possible single-line contingencies. This methodology is extended for contingency ranking. The effectiveness of the proposed method is demonstrated on two IEEE test power systems. In [11], a supervised learning approach has been proposed for fast and accurate power system security assessment and contingency analysis. In [11], feed-forward artificial neural network has been employed that uses pattern recognition methodology for security assessment and contingency analysis. In [12], a process of deriving decision trees for security assessment of multiple contingency in power system has been proposed. In [12], a newly developed graphical index has been proposed for group contingencies in order to obtain efficient decision trees for multiple contingences. The method has been illustrated on the Brittany region of French power system to derive decision rules against voltage collapse problems. In [13], a fast contingency algorithm for transient stability monitoring has been proposed and implemented in the KEPCO system. In [13], for screening stable cases, a new generator-grouping index has been proposed to identify critical generators. The test results showed that the proposed method can evaluate the first swing stability in a short time with reliable accuracy.

In this paper, three neural networks are represented to estimate LMPs, bus voltage magnitudes, and angles in normal conditions and different contingencies in the power system. The training of neural networks is carried off-line using simulated data. Results on two IEEE test systems show that predicted quantity comparable in accuracy to actual values and maximum absolute error is 10^{-3}. In this paper, in order to rank the contingencies, network security indices (voltage violation and line flow violation) and economic indices (locational marginal price and congestion cost) have been considered simultaneously. Network security and economic indices are calculated easily making use of estimated quantities (LMPs, bus voltage magnitudes, and angles). The efficiency of each of these contingencies was calculated using Stochastic Frontier Analysis (SFA), and this index was employed for ranking. Considering the proposed formulation for stochastic frontier analysis, the efficiency of a contingency will be higher if the calculated indices for that contingency are higher. More efficiency leads to increased severity of the contingency, and shows that the contingency has concurrently more affected network security and economic indices. The proposed algorithm can be applied to on-line contingency ranking as it is unaffected for any change in load/generation. To the best of authors' knowledge, these methods (neural network and SFA) have not been used to rank the power system contingency.

This paper is organized as follows. Section 2 presents the performance indices for contingency ranking. Section 3 presents the proposed algorithm. Section 4 details the application and presents the obtained results. Finally, Section 5 presents the concluding remarks.

2. Performance indices for contingency ranking

By experience, it is known that the ranking results depend highly on the operating index definition used to measure the severity of a contingency. Also, the choice of parameters in operating index definition depends on the usage of ranking results. As an example, if the ranking results are to be used for voltage stability issue, it is necessary to employ bus voltage and voltage stability margin parameters in index definition. In power transmission network management and planning, the line flow parameter is generally used. While bus voltage angles and critical clearing time are used to define index in transient stability problem, voltage violations [9,10,14] and line flow violations [9,10,15] are proposed as indicators of network security. The network security and economical indices should be considered when dealing with market environment. Locational Marginal Price (LMP) is the best economical signal to completely illustrate the market operation. Using LMP, the power consumers and producers experience real energy price in their location, and hence, LMP plays a significant role in system management.

In this paper, in order to evaluate the severity of important contingencies in the deregulated network, the network security and economic indices are considered together. The definitions related to these indices are as follows:

2.1. Voltage violation index

The most common index for voltage violation is [10]:

$$\mathrm{PI}_V = \sum_{j=1}^{nb} w_j \left| \frac{\Delta V_j}{K_j^V} \right|^{2m}, \tag{1}$$

$$K_j^V = \left(V_j^{\mathrm{Max}} - V_j^{\mathrm{Min}} \right)/2, \tag{2}$$

$$\Delta V_j = \left(V_j - V_j^{\mathrm{norm}} \right), \tag{3}$$

where PI_V is performance index of voltage violation, V_j^{Max} (V) and V_j^{Min} (V) are over-voltage and under-voltage limits, respectively. V_j^{norm} (V) is a user specified for bus j, and V_j (V) is post-contingency voltage magnitude for bus j. Also, W_j is a weighting factor for bus j, nb is the number of load buses, and m is a positive integer to reduce masking effects.

There is no explicit indication of how to select weighting factors and value of exponent (m). These factors are selected on the basis of experience with the system and on the relative importance placed on the various kinds of limit violation [16]. Masking effect can be avoided by using higher order performance indices ($m > 1$). In [17], an algorithm has been proposed for selecting the set of weighting factors using decision theory in order to improve the effectiveness of contingency ranking method. In [1], a novel approach called fuzzy logic-based analytical hierarchy process has been applied to adjust the appropriate and unequal values for weighting factors in contingency ranking.

2.2. Line flow violation index

The most common operating index for line flow violation is [10]:

$$\mathrm{PI}_{\mathrm{MVA}} = \sum_{j=1}^{nl} W_i \left(\frac{S_i}{S_{ni}} \right)^{2m}, \tag{4}$$

where PI_{MVA} is performance index of line flow violation, S_i (MVA) and S_{ni} (MVA) denote the apparent load and apparent power overload limits of line i, respectively. W_i is a weighting factor for line i, and nl is the total number of lines, respectively. m is a positive integer number used to avoid masking effect by increasing its value.

2.3. Locational Marginal Price (LMP) index

By definition, Locational Marginal Price (LMP) index for a bus is the minimum excess production cost needed to feed 1 MW extra load in the bus without violating transmission constraints; hence, it depends on the cost suggested by producers, market rules, and transmission constraints. LMP is one of the most important indications of market price which sheds light on the matter of the power market. One of the measures of competition level of the market based on LMP is to investigate the distribution of LMP. In a fully competitive market, all producers and consumers sell/buy electricity with the same price, meaning that in all buses, the price is the same and price profile is completely uniform, and there is no limitation for consumers on buying electricity from any desired producer. In practice, however, due to the transmission constraints and line losses, the LMPs of the buses cannot be the same, but still a more uniform LMP profile indicates more competition in market. Here, this index is used to evaluate contingencies, such that a more important contingency is defined to be the one which increases LMPs standard deviation. The distribution of bus prices is calculated as:

$$\mathrm{PI}_{\mathrm{LMP}} = \mathrm{Std}(\mathrm{LMP}_i), \tag{5}$$

where LMP_i ($/MWh) and Std represent the LMP ($/MWh) of bus i and standard deviation, respectively.

2.4. Congestion cost index

Congestion cost is another economic index based on LMP. Transmission congestion occurs when there is not enough transmission capability to support all requests for transmission services. The congestion cost of the whole system is the summation of all congestion costs of lines. It can be calculated as:

$$\mathrm{PI}_{\mathrm{CON}} = \sum_{j=1}^{nl} (\mathrm{LMP}_{j1} - \mathrm{LMP}_{j2}) \times P_j, \tag{6}$$

where LMP_{j1} ($/MWh) and LMP_{j2} ($/MWh) are the LMPs at the two ends of the line j, and P_j (MW) is the active power in line j.

3. The proposed algorithm

The algorithm is proposed through the following steps:

1. A large number of load patterns (active and reactive powers at all buses) are generated randomly;
2. AC load flows are performed for all load patterns, and all the single-line outage contingencies and the performance indices are calculated;
3. Three neutral networks are trained to predict LMP, voltage magnitude, and voltage angle;
4. During testing, the efficiency of each contingency is evaluated using the stochastic frontier analysis;
5. The contingencies are ranked based on efficiency values.

3.1. Stochastic frontier analysis

Stochastic frontier analysis is a parametric method used to estimate the efficient frontier and efficiency scores. The theory of stochastic frontier production functions was originally proposed by Aigner et al. [18] as well as Meeusen and van den Broeck [19]. This approach requires the definition of an explicit production or cost function and recognizes the possibility of stochastic errors. This is caused by an underlying assumption splitting the error term into a stochastic residuum (noise) and an inefficiency term. The statistical noise is assumed to follow a normal distribution, and the inefficiency term, u_i, is generally assumed to follow either a half-normal or truncated normal distribution. Hence, the mathematical expression of the production process is [20]:

$$Y_i = x_i\beta + (v_i - u_i)\ldots\ \ldots\ \ldots\ \ldots\ i = 1, ..., n, \tag{7}$$

where:

- Y_i Output (or the logarithm of output) of the ith firm,
- x_i $k \times 1$ vector of input quantities of the ith firm,
- β Vector of parameters to be estimated,
- v_i Random variables, which are assumed to be i.i.d. $N(0, \sigma_v^2)$, independent of u_i,
- u_i Non-negative random variables, usually assumed to be half normal distributed, thereby accounting for individual technical inefficiency.

The SFA technique can be used to predict efficiency scores of models involving multiple outputs by estimating input distance functions (see [21]). Translog form of input distance function is shown in Eq. (8):

$$\begin{aligned} -\ln(x_{Ki}) =& \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} \\ &+ \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} \\ &+ \sum_{n=1}^{M}\sum_{k=1}^{K-1} \beta_k \ln\left(\frac{x_{ki}}{x_{Ki}}\right) \\ &+ \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \beta_{kl} \ln\left(\frac{x_{ki}}{x_{Ki}}\right) \ln\left(\frac{x_{li}}{x_{Ki}}\right) \\ &+ \sum_{k=1}^{K-1}\sum_{m=1}^{M} \delta_{km} \ln\left(\frac{x_{ki}}{x_{Ki}}\right) \ln y_{mi} - \ln D_{Ii}, \end{aligned} \tag{8}$$

$M(m = 1, ..., M)$ and $K(k = 1, ..., K)$ are the number of outputs and inputs, respectively. $-\ln D_{Ii}$ can be interpreted as error term which reflects the difference between the observed data realizations and the predicted points of the estimated function. $-\ln D_{Ii}$ is rewritten as $v_i - u_i$. The relationship between technical efficiency and $-u_i$ is defined as $\mathrm{TE}_i = \exp(-u_i)$ [22] where TE_i represents the technical efficiency. The efficiency scores are bounded between 0 and 1; a value of 1 indicates relative efficiency.

In this paper, the voltage violation index (PI_V) and line flow violation index ($\mathrm{PI}_{\mathrm{MVA}}$) are considered as the inputs, while outputs are the LMP index ($\mathrm{PI}_{\mathrm{LMP}}$) and congestion cost index ($\mathrm{PI}_{\mathrm{CON}}$). The efficiency of each contingency, illustrating its severity, is then calculated based on these values.

3.2. Neutral network

The generic diagram of the Radial Basis Function (RBF) neutral network employed in this paper is shown in Figure 1 [10]. The RBF model used here is composed of an input array and two layers (one hidden and one output layers). Also, in this network, a Gaussian function is employed, which has the highest output when the input variables are closest to the center position and decreases monotonically as the distance from the center increases. Let X_p be the input array with component $x_{1p}, x_{2p}, ..., x_{rp}$. The output of the ith RBF unit in the hidden layer, which is $y_i(X_p)$, can be calculated using Eq. (9):

$$y_i(X_p) = \exp\left(-\frac{\sum_{j=1}^{r}[X_{jp} - \hat{X}_{ji}]^2}{\sigma_i^2}\right). \tag{9}$$

In Eq. (9), X_{jp} is jth input pattern, p, and $\hat{X}_{ji}$ is the center of ith RBF unit, U_i for the jth input variable.

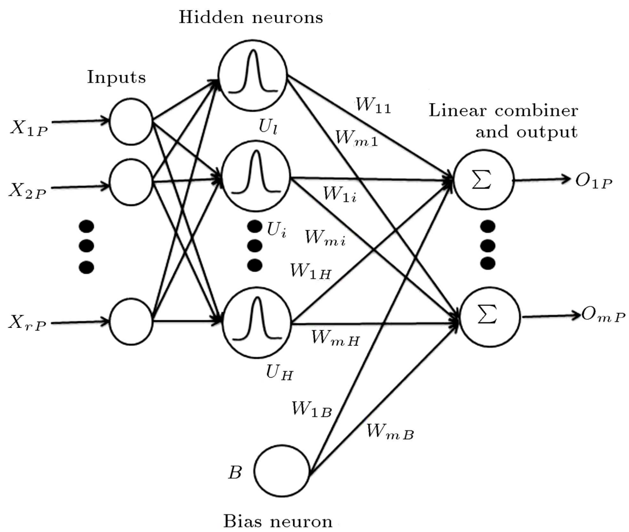

Figure 1. The diagram of the RBF neutral network [10].

Also, σ_i is the width of ith RBF unit, U_i. The output layer consists of a linear combiner whose output is presented in Eq. (10):

$$O_{mp} = \sum_{i=1}^{H} W_{mi} y_i(X_p) + W_{mB}, \tag{10}$$

where H is the number of hidden RBF units, O_{mp} is the output of the mth node of output layer for pth input pattern, W_{mi} is the weight between ith RBF unit, U_i and mth output node, and W_{mB} relates to the bias in mth output node in the linear output layer.

In this paper, the Orthogonal Least Squares (OLS) algorithm is used to train and build an RBF neutral network. OLS algorithm is a structure identification algorithm and builds a suitable network structure in an intelligent way during learning. It chooses appropriate RBF centers as neurons and trains the patterns one after the other until it reaches a specified error.

In this paper, three RBF neutral networks are designed for normal conditions and every contingency. Each input pattern includes active injection, P, in all buses except the slack bus and reactive injection, Q, in all load buses. Also, the patterns consisting of zero or constant values are excluded from the input patterns. Each input pattern, $[x]$, is represented as:

$$[x] = [P_{G1}, ..., P_{Gg}, P_{L1}, ..., P_{Ln}, Q_{L1}, ..., Q_{Ln}] . \tag{11}$$

For the voltage predictor, the output vector, $[V]$, includes all the load bus voltage magnitudes:

$$[V] = [V_{L1}, ..., V_{Ln}] . \tag{12}$$

The angle predictor builds the voltage angles, $[\theta]$, in all buses except the slack bus as:

$$[\theta] = [\theta_{G1}, ..., \theta_{Gg}, \theta_{L1}, ..., \theta_{Ln}] . \tag{13}$$

Finally, in the LMP predictor, the LMP values in all buses form the output vector [LMP]:

$$[\mathrm{LMP}] = \Big[\mathrm{LMP}_{sk}, \mathrm{LMP}_{G1}, ..., \mathrm{LMP}_{Gg}, \mathrm{LMP}_{L1}, ..., \mathrm{LMP}_{Ln}\Big], \tag{14}$$

where G is the generator bus, g is the number of generators in the power system, L is the load bus, n is the number of load buses, and sk is the slack bus in the power system.

4. Simulation test results and discussion

In this paper, MATLAB coding is developed to validate the proposed algorithm. Load flow analysis has been carried out using MATPOWER [23], and the estimated parameters of the distance function (for calculating efficiency) are calculated by using the Frontier 4.1 software by Coelli (1994) [24]. The proposed algorithm is tested on IEEE 14-bus and 30-bus power systems. In this paper, only the single-line outages are considered, and the RBF neutral networks are designed to estimate the post-contingency LMP, voltage magnitude, bus angles for every possible contingency in the test systems. In normal operating conditions, for each bus, 1000 load patterns are randomly generated by perturbing the load on each bus in the ranges of -80% to 120% of the base case. Similarly, for each line outage, 1000 patterns of bus injection (in the range -80% to 120% of the base case) are randomly generated for 1000 different operating conditions in both systems. Among the 1000 produced patterns for each system, 750 patterns are randomly chosen and saved for training, and the remaining 250 ones are marked to be used as test patterns.

In this paper, all weighting factors are assumed to be equal. It is observed from simulation that for $m = 4$ (the value of exponent), masking effect has been removed for IEEE 14-bus and 30-bus test power systems. We use three training algorithms, such as Levenberg-Marquardt, quasi-Newton, and orthogonal least squares, for the two case studies. The LM algorithm is found to be faster than other algorithms in training period. Results have shown that we obtain a lower absolute error for orthogonal least squares than for other algorithms. As mentioned in the paper, in the proposed method, the training of neural networks is carried out off-line. In summary, orthogonal least squares algorithm can be used as the best algorithm for the modeling and prediction of quantities for the two case studies. Therefore, in this paper, the Orthogonal Least Squares (OLS) algorithm is used to train and build an RBF neutral network.

4.1. IEEE 14-bus system

The IEEE 14-bus system consists of 9 PQ buses, 4 PV buses, a slack bus, and 20 lines. Three neural networks are designed for this system to predict angle, LMP, and voltage magnitude. In these networks, the LMP, voltage magnitude, and angle predictors predict the LMP at all buses, voltage magnitude at all 9 PQ buses, and voltage angle at all buses except the slack bus, respectively. The inputs are active powers in buses 2 to 14, and reactive power in buses 4, 5, 7, 9, 10, 11, 12, 13, and 14 results in 22 elements in the input patterns. There is no input reactive power in buses 2, 3, 6, and 8 as they are considered as PV bus. Also, the active and reactive powers at bus 1 are not considered as input since it is a slack bus. Therefore, the LMP predictor consists of 22 neurons in input layer and 14 neurons in output layer, showing LMP values for all buses. Similarly, the voltage magnitude predictor is composed of 22 and 9 neurons in input and output layers, respectively, to present voltage magnitudes in 9 PQ (load) buses, while the angle predictor uses the same 22 input neurons and 13 output neurons representing 13 PV and PQ buses. Maximum absolute errors in the estimated voltage magnitude and angle in each outage case are presented in Table 1. The errors in estimated LMPs, voltage magnitudes, and angles of buses have been tested for all 250 cases, yielding a maximum error of 10^{-3}. In this network, only 19 line outages are feasible. Table 2 shows calculated network security and economical indices for each contingency. The contingency efficiencies have been calculated by the stochastic frontier analysis, presented in column 6 of the Table 2. The minimum and maximum efficiencies correspond to contingencies 10 and 1, respectively. The last column of the Table 2 presents the ranking of each contingency. The more efficient a contingency is, the stronger and higher ranked it will be. Since no temperature limitation on transmission lines is considered in this network, the line flow violation index for all contingencies is zero, and it is not presented in Table 2. For example, consider contingency 1 where the line between buses 1 and 2 is out of the network. The calculated values for voltage, LMP, and congestion cost indices are 9.28, 1.97, and 1137, respectively. The efficiency of this contingency is calculated to be 0.96, and since it has higher efficiency than other contingencies, it

Table 1. Summary of voltage magnitude and angle maximum absolute errors for all test cases (IEEE 14-bus system).

Contingency no.	Voltage magnitude	Voltage angle
1	6.58E-04	3.36E-04
2	5.72E-04	1.13E-03
3	1.15E-03	3.83E-04
4	1.19E-03	7.59E-04
5	2.80E-04	1.05E-03
6	7.35E-04	1.34E-03
7	6.68E-04	1.44E-03
8	9.69E-04	8.21E-04
9	1.06E-03	2.08E-04
10	1.13E-03	2.24E-04
11	4.14E-04	3.86E-04
12	1.02E-03	1.26E-03
13	9.83E-04	3.81E-04
14	2.44E-04	1.22E-03
15	1.78E-04	3.65E-04
16	7.48E-04	1.39E-03
17	1.44E-03	5.25E-04
18	5.11E-04	2.95E-04
19	8.78E-04	3.77E-04

Table 2. Summarizing the results of the proposed algorithm on IEEE 14-bus system.

Contingency no.	LO[a]	PI_V	PI_{LMP}	PI_{CON}	Efficiency	Rank
1	**1-2**	**9.2792**	**1.9739**	**1137.00**	**0.9618**	**1**
2	1-5	6.9086	1.5745	956.28	0.6637	18
3	2-3	9.7076	1.4151	786.00	0.8011	11
4	2-4	9.8271	1.3008	815.58	0.8566	9
5	2-5	10.1780	1.2288	782.18	0.9027	5
6	3-4	10.0960	1.0954	729.72	0.8713	8
7	4-5	9.2019	1.3287	796.90	0.7732	13
8	4-7	10.2670	1.1428	739.08	0.9343	3
9	4-9	9.6720	1.1134	737.81	0.7802	12
10	**5-6**	**5.9353**	**1.3873**	**757.15**	**0.6207**	**19**
11	6-11	8.5242	1.1480	740.92	0.7187	16
12	6-12	9.1877	1.2607	749.98	0.7431	15
13	6-13	8.2285	1.5301	803.96	0.6956	17
14	7-9	8.7871	1.2341	800.53	0.7525	14
15	9-10	10.0690	1.1905	752.19	0.8827	7
16	9-14	10.8540	1.4938	791.84	0.9494	2
17	10-11	10.1750	1.1084	732.12	0.8979	6
18	12-13	10.3600	1.1075	734.89	0.9159	4
19	13-14	9.9044	1.1652	739.16	0.8179	10

[a]LO: Line outage from bus number to bus number.

is ranked 1st. indeed, this contingency is the strongest and worst one in the network regarding security and economical indices. The voltage violation index for contingency 16 (outage of the line between buses 9 and 14) is 10.85, which is the worst contingency based on voltage violation index (as one of the network security indices), but since economic indices are also considered here, it is ranked 2nd. In this system, the contingency 10 (outage of the line between buses 5 and 6) has the lowest efficiency, and therefore, is ranked last. In this contingency, the voltage violation index is 5.93, LMP index is 1.39, and congestion cost index is 757.

4.2. IEEE 30-bus system

The IEEE 30-bus system consists of 24 PQ buses, 5 PV buses, a slack bus, and 41 lines. The three aforementioned neural networks for prediction of angle, LMP, and voltage magnitude are designed for this system. Here, the LMP, voltage magnitude, and angle predictors predict the LMP for all buses, voltage magnitude for all 24 PQ buses, and voltage angle for all buses except the slack bus, respectively. The inputs are active power for buses 2 to 30 and reactive power for all PQ buses, meaning that there are 44 elements in input patterns. If the power injection of some buses is zero, they are not considered in the input pattern. The active and reactive powers in bus 1 are not considered as input, since it is the slack bus. Hence, the LMP predictor includes 44 and 30 neurons in the input and output layers, respectively, showing the LMP values for all buses. The voltage magnitude predictor consists of 44 neurons in input layer and 24 ones in the output layer, presenting the voltage magnitudes for 24 PQ (load) buses. Similarly, the angle predictor is composed of 44 input neurons and 29 output neurons (standing for total number of 29 PV and PQ buses, except the slack bus). Maximum absolute errors in the estimated voltage magnitude and angle in each outage case are presented in Table 3. The errors in estimated voltage magnitudes and angles for each bus are tested on all 250 cases, resulting in a maximum error of 10^{-3}. In this case, the retrained RBF neural networks in 250 test patterns are performed for each of 34 feasible outages in this case.

Table 3. Summary of voltage magnitude and angle maximum absolute errors for all test cases (IEEE 30-bus system).

Contingency no.	Voltage magnitude	Voltage angle
1	2.29E-03	2.40E-03
2	9.13E-03	1.23E-03
3	1.52E-03	1.84E-03
4	8.26E-03	2.40E-03
5	5.38E-03	4.17E-03
6	9.96E-03	4.97E-04
7	7.82E-04	9.03E-03
8	4.43E-03	9.45E-03
9	1.07E-03	4.91E-03
10	9.62E-03	4.89E-03
11	4.63E-05	3.38E-03
12	7.75E-03	9.00E-03
13	8.17E-03	3.69E-03
14	8.69E-03	1.11E-03
15	8.44E-04	7.80E-03
16	4.00E-03	3.90E-03
17	2.60E-03	2.42E-03
18	8.00E-03	4.04E-03
19	4.31E-03	9.65E-04
20	9.11E-03	1.32E-03
21	1.82E-03	9.42E-03
22	2.64E-03	9.56E-03
23	1.46E-03	5.75E-03
24	1.36E-03	5.98E-04
25	8.69E-03	2.35E-03
26	5.80E-03	3.53E-03
27	5.50E-03	8.21E-03
28	1.45E-03	1.54E-04
29	8.53E-03	4.30E-04
30	6.22E-03	1.69E-03
31	3.51E-03	6.49E-03
32	5.13E-03	7.32E-03
33	4.02E-03	6.48E-03
34	7.60E-04	4.51E-03

Table 4 represents the network security and economical indices calculated for each contingency in the 30-bus system. The efficiencies of the contingencies are calculated using the stochastic frontier analysis, which is shown in column 6 of the Table 4. The lowest and highest efficiencies correspond to the contingencies 29 (outage of the line between buses 24 and 25) and 9 (outage of the line between buses 6 and 7), respectively. The last column of this table represents the ranking of all contingencies. The minimum and maximum efficiencies are 0.496 and 0.953, respectively. The average efficiency for the 30-bus network is calculated to be 0.818. In the 30-bus network, contingency 9 is the worst one. For this contingency, the voltage violation index is 15.84, line flow violation index is 237, LMP index is 0.786, and the congestion cost index is 183.3. The efficiency of this contingency is 0.953, and it is ranked 1st, meaning that it is the strongest and worst contingency in the network based on network security and economical indices. Contingency 29 (outage of the line between buses 24 and 25) is ranked last, where the voltage violation index is 8.41, the line flow violation index is 55.6, the LMP index is 0.12, and the congestion cost index is 23.1, which are much less than the ones of contingency 9.

5. Conclusion

In this paper, the combination of neural networks and stochastic frontier analysis is employed to rank the contingencies of the system. The neural network method is used to estimate magnitudes and angles of all system buses in order to determine line flow and LMP. Hence, three neural networks are represented to estimate LMPs, bus voltage magnitudes and angles in normal conditions and different contingencies in the power system. Here, the network security indices (voltage violation and line flow violation indices) and economical indices (LMP and congestion cost indices) are simultaneously considered to rank the contingencies. The efficiencies of each of these contingencies were calculated using stochastic frontier analysis, which was used in their ranking. The proposed algorithm for contingency ranking was performed on IEEE 14-bus and 30-bus power test systems, where the simulation results show the high performance of the algorithm.

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Table 4. Summarizing the results of the proposed algorithm on IEEE 30-bus system.

Contingency no.	LO[a]	PI_V	PI_{MVA}	PI_{LMP}	PI_{CON}	Efficiency	Rank
1	1-2	9.599	188.58	0.2835	64.312	0.7978	24
2	1-3	9.131	206.05	0.3197	73.909	0.8909	12
3	2-4	9.4075	200.75	0.3264	73.562	0.8288	19
4	2-4	8.98	204.32	0.3302	74.585	0.8964	11
5	2-5	10.271	191.8	0.2795	64.464	0.8533	16
6	2-6	8.947	193.48	0.2854	65.002	0.8035	23
7	4-6	10.578	161.52	0.2468	56.687	0.7718	27
8	5-7	10.248	190.47	0.28	64.021	0.8304	18
9	**6-7**	**15.842**	**237.03**	**0.7862**	**183.3**	**0.9535**	**1**
10	6-9	12.123	202.42	0.2503	57.802	0.7794	26
11	6-10	13.517	194.07	0.2685	60.494	0.5897	32
12	9-10	12.706	202.42	0.2528	57.803	0.7849	25
13	4-12	14.333	241.59	0.5324	121.07	0.9274	4
14	12-14	10.544	200.28	0.3185	71.257	0.8769	13
15	12-15	12.63	213.66	0.3817	85.347	0.9098	8
16	12-16	19.713	208.58	0.5354	123.46	0.9460	2
17	14-15	9.3161	189.38	0.2893	63.968	0.8248	20
18	16-17	13.022	195.67	0.4055	91.332	0.9109	7
19	15-18	16.495	194.3	0.4155	95.966	0.9139	6
20	18-19	12.636	186.2	0.366	82.658	0.9016	9
21	19-20	10.59	257.66	0.2972	66.245	0.8701	14
22	10-17	11.117	202.02	0.2855	64.301	0.8494	17
23	10-21	9.2113	179.55	0.2826	62.672	0.8187	21
24	10-22	17.234	228.73	0.7217	167.13	0.9319	3
25	21-22	10.093	198.3	0.2645	62.296	0.7416	29
26	15-23	10.716	190.12	0.2558	62.945	0.6784	30
27	22-24	8.7469	169.3	0.2048	47.973	0.5238	33
28	23-24	19.838	203.75	0.4485	100.69	0.9247	5
29	**24-25**	**8.4129**	**55.619**	**0.1208**	**23.122**	**0.4959**	**34**
30	25-27	14.412	55.89	0.1601	16.149	0.6581	31
31	27-29	10.941	231.85	0.3115	69.935	0.8701	15
32	27-30	11.132	254.49	0.3126	71.068	0.8965	10
33	29-30	8.4816	208.59	0.3249	72.224	0.8116	22
34	6-28	15.436	101.66	0.1516	16.554	0.7653	28

[a]LO: Line outage from bus number to bus number.

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