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VOLTAGE SECURITY MARGIN ENHANCEMENT USING GENERATION RESCHEDULING AND LOAD SHEDDING WITH AN ARTIFICIAL NEURAL NETWORK

S.H. Fatemi Nejad M.T. Ameli

Electrical Engineering Department, Power and Water University of Technology, Tehran, Iran
h.fatemi64@yahoo.com, ameli@pwut.ac.ir

Abstract- The occurrence of the recent nationwide blackouts in some major power networks of the world indicates the weakness of current control and protection systems. Implementation of appropriate control and protection plans is necessary, then, to prevent such future occurrences. In this paper, an algorithm is presented which can evaluate and improve voltage stability by using an online artificial neural network (ANN). A voltage security margin (*VSM*) index is used to evaluate voltage stability by dividing the operating points into two groups: safe and unsafe. Generally, the algorithm consists of two stages: online and offline. Initially, though, in the offline stage, the *VSM* of an operating point which is labeled as unsafe is turned back to a secure level by changing the production pattern of generators and, if necessary, load shedding using the sensitivity analysis method. The ANN is then trained using different input variables with the required control actions in order to improve the voltage conditions of the system. In an online stage, the ANN can estimate the required controlling action which would return the system to a proper voltage within a safe time period. For real-time applications, network information can be obtained from Phasor Measurement Units (PMUs).

Keywords: Voltage Stability, Voltage Security Margin, Generation Rescheduling, Load Shedding, Artificial Neural Network (ANN), Phasor Measurement Units (PMUs).

I. INTRODUCTION

Voltage stability problems have become one of the main concerns for power system operators in recent years for many reasons, including rapid growth of load and economic and environmental constraints. Today, deregulation of the electricity industry has served to intensify the focus on the constraints. In other words, due to economic issues, transmission lines tend to be operated at peak capacity. This, though, increases the risk of instability and decreases the operator's ability to maintain system security. What is needed, then, is the ability to determine an adequate safety margin around the point of instability.

There is no shortage of methods for preventing the collapse of a voltage system by improving the voltage conditions of the network. These include changing of generator production patterns, tap changing under load transformers, use of reactive power compensators, regulation of a generator's AVR and load shedding. Verbic and Gubina [1] present an algorithm to protect the system against voltage instability based on local phasor data. In the algorithm, the rate variation of line apparent power is used as an instability criterion. Kolluri et al. [2] present a voltage protection scheme based on SCADA data. This plan identifies voltage instability and automatically attempts to load shed. Asghari and Sadeh [3] used generator AVR regulation and load shedding in order to improve the voltage security margin.

Nakawiro and Erlich [4] and Amraee et al. [5] use load shedding in order to meet operational limits and provide a minimum voltage stability margin. Chakrabarti and Jeyasura [6-7] changed the generator production pattern in order to improve the voltage stability margin. Echavarren et al. [8] present a method for determining the injection pattern of reactive power that can increase the loading level of a network. Pessanha et al. [9] present a method for enhancing the loading level of a network by developing transmission lines. Capitanescu [10] presents a preventive controlling scheme dealing with voltage instability for changing the pattern of production and load shedding. This allowed him to control the operation using calculations of the voltage stability margin sensitivity with respect to control parameters.

Pavlyuchenko et al [11] present the requirements of intellectual reactive power and voltage control, and also the main principles of its mathematical realization on the basis of artificial intelligence methods are considered. Lyubchenko et al. [12] has been solved for single distributive substation by methods of artificial intelligence on the one hand to simplify the decision and on the other hand to use the effective methods.

Again, there are different methods for preventing voltage instability. However, the aforementioned methods, which operate locally and are based on regional data, do not have the ability to prevent a global collapse; in some cases, they can even cause an increase in such events. Sensitivity analysis is one of the more useful methods widely used to determine the changes in the network needed to improve voltage conditions. However, calculation of these changes using the sensitivity analysis method is a time-consuming process; hence, its use on large power systems is generally not possible. This is not an issue in the offline mode and used regularly.

In the online mode, it is very time consuming. Therefore, in order to present an online algorithm for evaluating voltage stability based on this method, the development of intelligent methods of data seeking was inevitable. Among these intelligent methods is one based on artificial neural networks (ANNs). The ANN is an automatic learning, pattern recognition technique whose applications have increased dramatically in a variety of disciplines over the last few decades. This technology offers characteristics such as fast response time in data mapping makes it suitable for online applications [13].

Another requirement for online implementation of the algorithm is the availability of necessary information throughout the network. In recent years, with development of new technologies in telecommunication systems and the arrival of new technologies in measuring network variables such as phasor measurements units (PMUs), measurement and sending of data on a network is possible with ever increasing accuracy and speed. Thus, assuming the availability of network data by PMU, ANN can be used to proactively estimate necessary changes for improving the voltage stability margin. The major advantage of using the ANN models is that they can capture the nonlinear characteristics of a system in order to avoid iterative procedures. Stated another way, with a quick estimate of the necessary changes in generator production patterns and the amount of load shedding, ANN can provide for the timely improvement in the voltage stability of a network.

II. INDEX USED TO ASSESS VOLTAGE STABILITY

In order to assess voltage stability, *P-V* curves, one of the most common methods for determining voltage static stability were used in this current study. The evaluation of voltage stability is based on the distance between the operating point and the critical point. For this purpose, an index under the name of voltage security margin (*VSM*) was defined. Based on this point, Sagar et al. [13] evaluated the voltage stability of the system. Generally, *VSM* is a function of variation in the load and the production pattern. As can be seen in Figure 1, the *VSM* is defined as follows:

$$VSM\,(\%) = \frac{P_{\max} - P_0}{P_{\max}} \times 100 \qquad (1)$$

Given the simplicity of this definition and the ease of understanding by system operators, the voltage stability margin as an index with general acceptance has been proposed in the evaluation of voltage stability.

The *VSM* can also be achieved using the continuation power flow (CPF) method. However, this method of calculating *VSM* is time consuming, making it less responsive for large power systems.

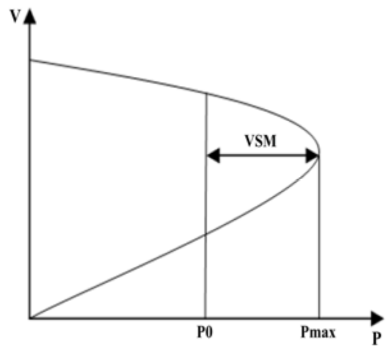

Figure 1. *P-V* curve

In this study, the authors used an ANN for estimating voltage stability based on the *VSM* index. At the top speed of PMUs, the information of these units can be used to provide the necessary data for the ANN in order to estimate the *VSM*. The *VSM*, then, that is required for safe operation of the network depends on the amount of tension value in the power system.

According to the definition, if a system has the ability to maintain its steady and transient voltage when dealing with an emergency condition, it can be said that the system has voltage security [13]. The levels of performance of a *VSM*, over different conditions of performance based on the Western System Coordinating Council (WSCC) standards, are shown in Table 1.

Table 1. WSCC Voltage stability criteria

Performance Level	Disturbance (1)	MW Margin (*P-V* Method)	MVAR Margin (*V-Q* Method)
A	Any element such as: One Generator One Circuit One Transformer One Reactive Power Source	≥5%	Worst case scenario
B	Bus Section	≥2.5%	50% of Margin Requirement in Level A
C	Any combination of two elements such as: A Line and a Generator A Line and a Reactive Power Source Tow Circuit Tow Transformers Tow Reactive Power Source	≥2.5%	50% of Margin Requirement in Level A

1. Margin for *N*-0 (base case) conditions must be greater than the margin for performance Level A

III. PROPOSED ALGORITHM

The occurrence of the recent nationwide blackouts in some major power networks of the world indicates the weakness of current control and protection systems. Implementation of appropriate control and protection plans, then, is necessary to prevent such occurrences. In order to prevent a voltage collapse under such conditions, precautions such as control of system coordination, accuracy and speed should be evaluated. In this paper, an online algorithm is presented to evaluate and improve the *VSM* for reducing the risk of voltage collapse in power systems. In order to evaluate stability, the *VSM* index is used. Generally, the algorithm consists of two online and offline stages. In the offline stage, an ANN is trained using different input variables along with the required control actions to improve the voltage conditions of the system. In the online stage, an ANN estimates the required controlling action necessary to return the system, in a timely manner, to its proper voltage. It is assumed that the necessary information from the PMU is available.

An ANN can be used as a precautionary and control operating estimator for the network, replacing the time-consuming and heavy, nonlinear computations of the CPF and sensitivity analysis methods. The ANN further prevents heavy, iterative numeral computation procedures by creating proper mapping between input and output quantities. For example, for the New England 39-bus test system, the proposed algorithm needs on average around 150 ms to estimate the necessary generation rescheduling or load shedding under a certain operating point, whereas the CPF and sensitivity analyses need around 20s to accomplish the same tasks under the same conditions. The computational time is estimated by Matlab's built-in tic/toc function running on an Intel Core i5 2.90 GHz computer. Therefore, the proposed algorithm is expected to estimate the generation rescheduling and load shedding in a much shorter time compared to a sensitivity analysis. For real-time applications, network information can be obtained from PMUs.

Figure 2 shows a flowchart of the proposed algorithm. According to the flowchart, the proposed algorithm consists of five stages that can be divided into two offline and online parts. These five stages can be described as follows:

1. Calculation of the *VSM* of the system in the offline mode and classification of the achieved operating point as safe or unsafe based on the WSCC instruction.
2. Improving the *VSM* of an unsafe operating point by changing the production pattern of the generators and load-shedding sensitivity analysis.
3. Training of the two ANNs with the following objects:
   a) Training the first ANN to estimate the system *VSM*.
   b) Training the second ANN to estimate the necessary changes in the power produced by the generators and load shedding to improve the *VSM*.
4. Using measurements obtained from the PMUs to evaluate the system *VSM* using the first ANN.
5. If necessary, a change in the power produced by the generators and load shedding is estimated to improve the *VSM* using the second ANN.

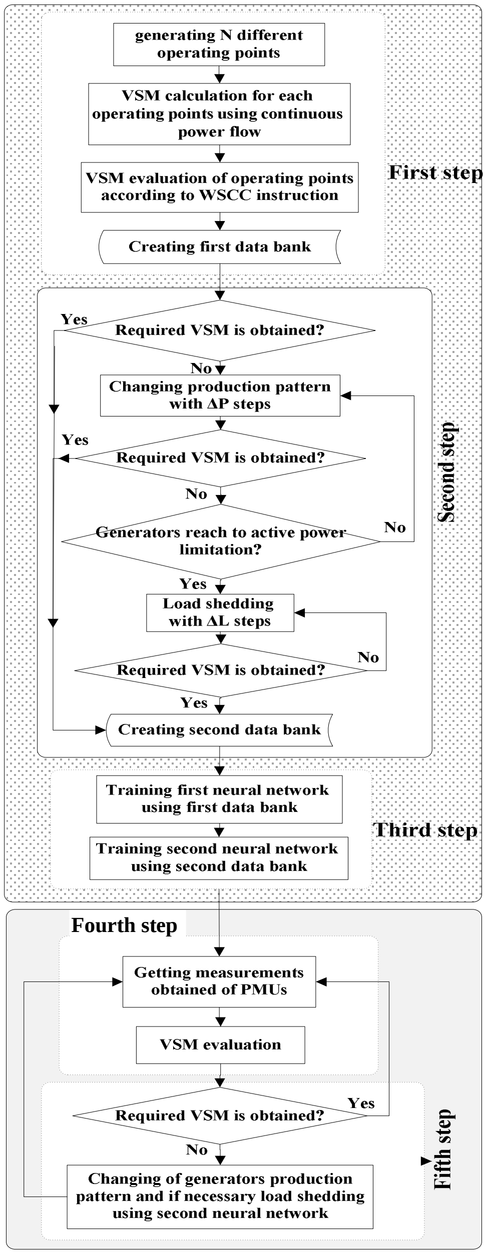

Figure 2. Proposed algorithm to improve the *VSM*

In this study, the New England 39-bus test system was used. This network has a total of 39 buses, 34 lines, 19 loads and 10 generators. In order to provide the necessary training samples, a wide range of system operating conditions from load level, load and production pattern and also network structure points of view should be created as these samples contain different states for the network. According to these cases, the final data bank includes 2,412 operating points of which 366 cases are labeled unsafe in terms of performance, with the rest labeled as safe. Considering all of the operating points, 1,809 samples were used for training and 603 were used as test data. Test data were selected to include different working areas. In this study, a DIgSILENT Power Factory 14 was used to simulate an IEEE 39-bus system. Then, using different operating states and output sensitivity analyses, the ANN was trained using Matlab.

IV. CASE STUDY

In defining the proposed algorithm, in order to assess its performance in improving the *VSM*, this scheme was applied to the New England 39-bus test system. In order to define different patterns of load and generating variation, thus creating different operating points, the network was divided into two areas (refer to Figure 3). In this division, it was expected that each region would be equal at production and basic load states.

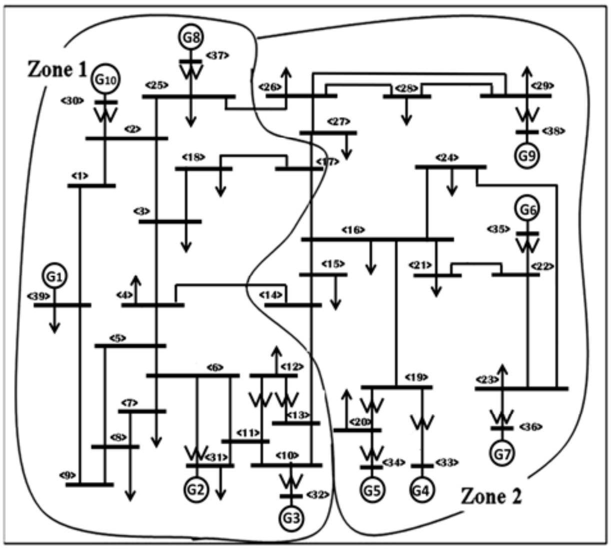

Figure 3. Single-line diagram of the IEEE 39 buses with areas considered

In the actual power system, regions can be considered as loads representing geographical boundaries and having similar climates. According to the areas considered, in order to define different operating points, the following three conditions were considered:

1. The total load and production in both regions increase with the same steps.
2. In the first areas, load and generation coefficients are considered constant and the entire load and generation of the second area increases with the same coefficients.
3. Load and generation coefficients in the second area are considered constant and the entire load and generation of the first area increases with the same coefficients.

The increase of load and generation continues until the occurrence of an event that causes a collapse of the entire voltage network. For each increase in load and generation, outage lines and generators based on N-1 contingency was considered as an event.

A. Effect of Different Inputs on the Accuracy of the Proposed Algorithm

To study the effect of different inputs on the accuracy of the proposed algorithm in estimating the required generations reschedule and load shedding, resulting in the selection of the optimum ANN type, where the input variables of the ANN are selected according to Table 2.

In order to better examine ANN error, Equations (2) and (3) were used [15]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(V_{act} - V_{est})^2} \tag{2}$$

$$MAPE(\%) = \frac{100}{N} \times \sum_{i=1}^{n}\left|\frac{V_{act} - V_{est}}{V_{act}}\right| \tag{3}$$

where *RMSE* is Root Mean Squared Error, *MAPE* is Moving Average Percentage Error, V_{act} is the real value, V_{est} is the estimated value given by the algorithm, and N is the number of data points. Table 3 shows the accuracy of the ANN in estimating the value of generator production pattern changes and load shedding for different inputs.

Table 2. Variables used as inputs to the proposed algorithm

ANN	ANN input
ANN1	V, I, P_G, Q_G, FE
ANN2	V, I, P_G, Q_G
ANN3	V, I, FE
ANN4	V, I
ANN5	V, FE
ANN6	V

FE = Failed Element

Table 3. ANN accuracy according to different input variables for test data

ANN	*RMSE*	*MAPE* (%)
ANN1	3.4394	0.2905
ANN2	4.3193	0.3928
ANN3	4.0648	0.3648
ANN4	4.7559	0.3663
ANN5	5.4405	0.4543
ANN6	6.1213	0.4615

According to Table 3, it can be seen that ANN1 has the least amount of error. Figure 4 shows the accuracy of the proposed algorithm in estimating the amount of change in generator production patterns and load shedding. This figure shows the estimated values from ANN1 based on calculated values using the method of sensitivity analysis for 200 samples of test data. According to the figure, if the estimated amount is equal to the actual value, the output point lies on the bisector of the first and third quarters.

According to Table 3 and Figure 4, and considering the number of failed elements (FE) as one of the inputs, the ANN error decreases in the estimation of the amount of generator changing pattern and load shedding. For example, by considering the number of failed elements (in ANN1), the RMSE error of the test data is 3.4394; if the failed elements (in ANN2) are not considered, the RMSE error will be 4.3193. According to the table, it can also be seen that ANN1, where use from bus voltages, line current, generation production power and the number of failed elements are considered as inputs, has the lowest error. Therefore, the authors chose ANN1.

B. Results and Analyses

In order to analysis the performance of the proposed algorithm in terms of improving the *VSM*, the calculated *VSM* by CPF method is shown before and after applying the proposed algorithm for 50 of the test data. Outages were found in only one line or generator, resulting in a safe *VSM* of 5% (Table 1).

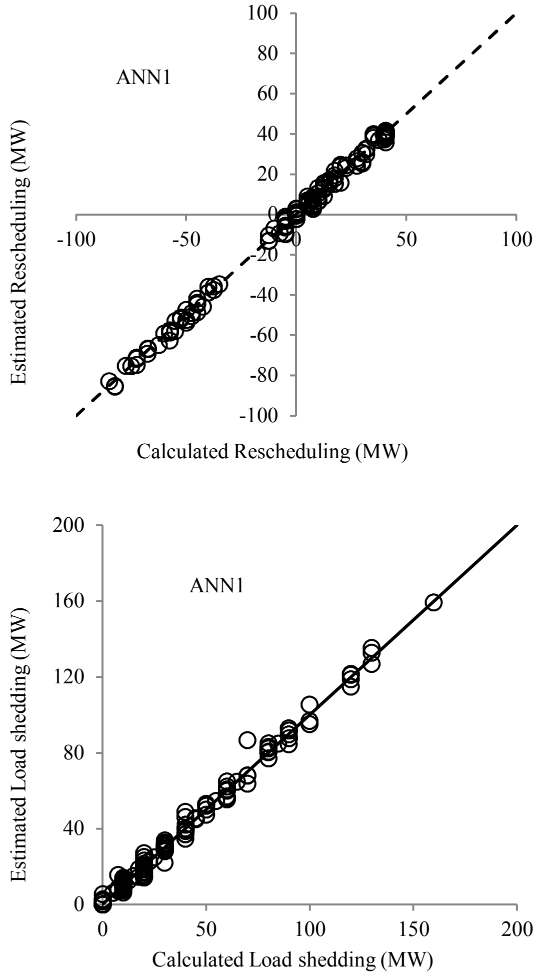

Figure 4. Proposed algorithm accuracy in estimation of generator production pattern changes and load shedding value for ANN1

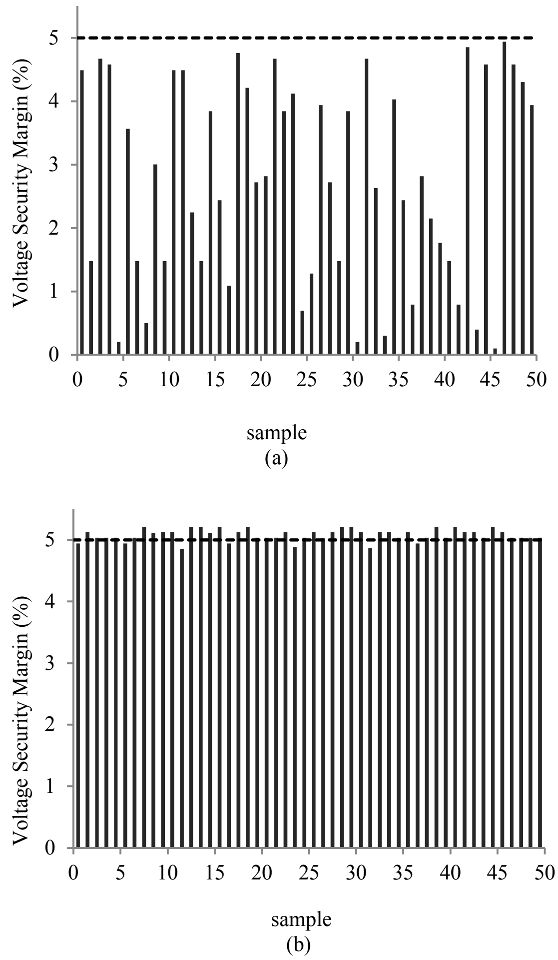

Figure 5. Voltage security margin (a) before applying the algorithm (b) after applying the algorithm

Table 4. The error of the proposed algorithm in improving the *VSM*

RMSE	0.106	*MAPE* (%)	1.672

Table 5. Selected operating point

		load ratio of region	
Operating point	Outage element	Zone 1	Zone 2
1	Gen. 2	1.42	1.42
2	Gen. 9	1.2	1.68
3	Gen. 6	1.2	1.72
4	Line 21-22	1.5	1.5
5	Line 21-22	1.25	1.6

According to Figure 5(b), it can be seen that after applying the proposed algorithm, the *VSM* approximately reaches a range of 5%, which is considered safe based on the WSCC standard. Table 4 shows the error of the proposed algorithm in improving the *VSM*.

In order to improve the analysis, five operating points were selected as samples from the test data (Table 5). Figure 6 shows the *VSM* by CPF method for the operating points before and after applying the proposed algorithm. According to the figure, the *VSM* - across all operating points before applying the proposed algorithm - is less than 5%, which is unsafe based on the WSCC standard. After applying the proposed algorithm, however, the VSM easily reaches the 5% level.

Table 6 shows the amount and location of the calculated load shedding by the sensitivity analysis (SA), estimated by the proposed algorithm (PA) for the operating points in Table 4. According to the table, the proposed algorithm accurately estimated the amount and location of load shedding. For operating points 4 and 5, no load shedding is needed; the VSM will return to a safe level just by changing the generator's production pattern. Table 7 shows the amount and location of the generator's production changes for operating points 4 and 5.

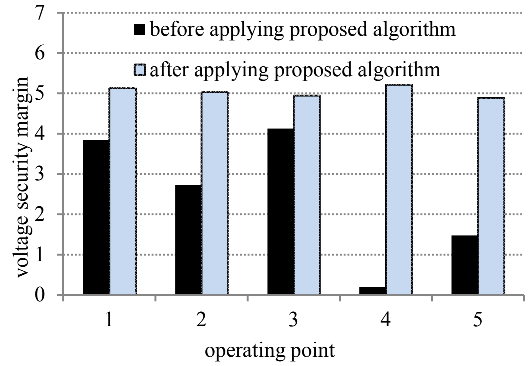

Figure 6. Improving the *VSM* using the proposed algorithm for selected operating points

Table 6. Calculated load shedding using the sensitivity analysis and the proposed algorithm

	Operating point 1		Operating point 2		Operating point 3	
Selected load	SA (MVA)	PA (MVA)	SA (MVA)	PA (MVA)	SA (MVA)	PA (MVA)
8	30	31.4	0	0	0	0
28	0	0	35	37.21	0	0
4	20	18.39	0	0	0	0
21	0	0	0	0	25	26.07

Table 7. Relocation of production calculated using the sensitivity analysis and the proposed algorithm

	Operating point 4		Operating point 5	
Selected Generator	SA (MW)	PA (MW)	SA (MW)	PA (MW)
3	40.625	37.77	40.625	40.625
4	0	0	12.5	12.38
6	-77.5	-78.86	0	0
7	0	0	-67.5	-65.32
5	27.5	26.17	31.75	30.53

Positive numbers indicate an increase and negative numbers indicate a decrease in production. According to Table 7, the proposed algorithm is quite accurate for the amount and location of generation rescheduling.

C. Performance Analysis of the Proposed Algorithm for Load Shedding and Considering Load Priority

Given the fact that loads on the network have different levels of importance, they can receive priority in the load-shedding stage. Figures 7 and 8 show the proposed capability of the algorithm in estimating the amount and cost of load shedding given the priority of the loads.

According to Figures 7 and 8, it can be seen that the proposed algorithm can estimate both value and cost of necessary load shedding with great accuracy in order to improve the voltage security margin of the network, while taking into account load priority.

Figure 9 shows the *VSM*, calculated by CPF, before and after applying the proposed algorithm for the operating points defined in Table 4. According to the figure, it can be seen that after applying the proposed algorithm, the *VSM* approximately reached the 5% level.

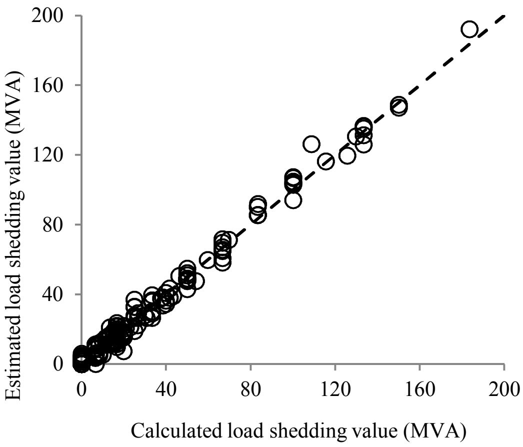

Figure 7. Proposed algorithm accuracy in estimating the load shedding value considering load priority

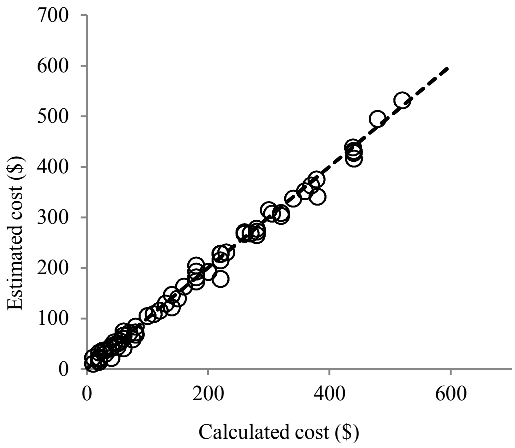

Figure 8. Proposed algorithm accuracy in calculating the load shedding cost considering load priority

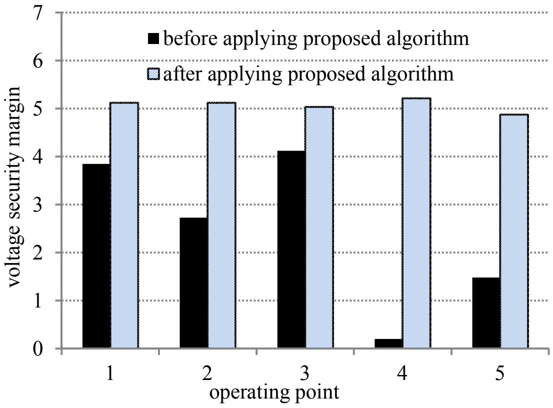

Figure 9. Improving the voltage security margin using the proposed algorithm for selected operating points and considering load priority

Table 8 shows the amount and location of load shedding calculated by the sensitivity analysis (SA) and estimated by the proposed algorithm for these operating points.

Table 8.Calculated load shedding using the sensitivity analysis and the proposed algorithm considering load priority

	Operating point 1		Operating point 2		Operating point 3	
Selected load	SA (MVA)	PA (MVA)	SA (MVA)	PA (MVA)	SA (MVA)	PA (MVA)
18	15	13.55	0	0	0	0
21	15	16.08	0	0	30	28.68
24	20	18.39	0	0	0	0
28	0	0	40	38.11	0	0
8	20	22.12	0	0	0	0

According to Table 8, the proposed algorithm can estimate the value of load shedding needed with great accuracy by considering load priority. As was mentioned for operating points 4 and 5, load shedding is not needed and the *VSM* can return the system to a safe level just by changing the generator's production pattern.

V. CONCLUSIONS

Results indicate that after applying the proposed algorithm to the network - to determine if changes in rescheduling or load shedding are needed - the *VSM* will be returned to a safe level.

Using information obtained from various simulations, it is clear that the proposed algorithm works properly in the estimation of generation rescheduling and optimum load shedding. Furthermore, considering the needed time for implementation of the algorithm (about 150ms), using this algorithm can also improve the reaction time of the *VSM*. After taking into account the priority of load shedding, results related to the amount and location of the needed load shedding indicate the capability of the algorithm to select optimal load shedding. For real-time applications, network information can be obtained from PMUs.

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BIOGRAPHIES

Hossein Fatami Nejad was born in Gachsaran, Iran on 1986. He received his B.Sc. degree in Electrical Engineering from Shahid Chamran University, Ahvaz, Iran, in 2008, and M.Sc. degree from Power and Water University of Technology, Tehran, Iran, in 2012. His research interests are in the areas of voltage stability and neural network.

Mohammad Taghi Ameli received the B.Sc. degree in Electrical Engineering from Technical College of Osnabrueck, Germany, in 1988, and the M.Sc. and Ph.D. degrees from Technical University of Berlin, Berlin, Germany, in 1992 and 1997, respectively. Since then he teaches and researches as Associate Professor in Electrical Engineering Department, Power and Water University of Technology, Tehran, Iran. He was general director of Iran Research and Technology Institute for Electric Machines for three years. His areas of research are power system simulation, operation, planning and control of power system, and usage of renewable energy in power system.