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VOLTAGE AND FREQUENCY MONITORING OF POWER SYSTEMS USING SUPERVISED SELF-ORGANIZING FEATURE MAPS.

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Abstract

This paper presents a new intelligent method for monitoring of static security of power system using the supervised self-organizing maps (SSOM) which are a development of the original SOM network that was proposed by Kohonen. The proposed method uses active and apparent power data of system buses under different operation conditions and contingencies and forms input-output maps classifying the buses in classes (safe, warning and alarm) according to their voltage and frequency. This method was applied to 230 kV Syrian power transmission system. Extensive simulation studies show that the proposed method provides accurate results under various system normal and abnormal conditions in a short time compared to traditional load flow calculation methods such as fast-decupled Newton Raphson.

Keywords: Power system static security, Self-organizing feature maps, Voltage stability, Frequency control, Buses clustering.

1. Introduction

Static security is defined as the ability of the system to reach a state within the specified secure region following a contingency (Swarup and Britto Corthis, 2013). A security assessment can be obtained by the conventional way that performs a static security analysis which evaluates the post-contingent steady state of the system without taking the transient behavior or any time-dependent variations in consideration. Power system stability can be broadly classified into rotor angle, voltage, and frequency stability. In this paper, we will discuss voltage and frequency stability.

The ability of power system to keep acceptable voltage values at all system buses during normal operation and also after the occurrence of disturbance is called voltage stability (Nizam 2010). Online voltage stability monitoring is very important in order to avoid voltage collapse which could cause a blackout when voltages decrease catastrophically and the system operator didn't take corrective actions to restore the voltage to its rated value.

Frequency stability refers to the ability of a power system to maintain steady frequency value following a severe disturbance between generation and load. This imbalance between the electrical load and the power supplied by generators lead directly to frequency deviation (Bevrani 2009). In this paper, frequency deviation considered as an important indicator of the imbalance between the generation and load.

The deviation in the system frequency (during normal operation) will cause the primary controllers of all generators subjected to this deviation to adjust the speed of governors within a few seconds. Whereas for a larger frequency deviation that happens during off-normal operation, a secondary control known as LFC (Load Frequency Control) will operate in addition to the primary frequency control. In this control, the amount of load shared by the generating stations in an area is determined by load dispatch center in a time period of a few seconds to a few minutes. However, for a critical load-generation imbalance accompanied by rapid frequency changes after a significant fault, the LFC system may unable to restore frequency, and further actions had to be made to restore frequency. This can be done using tertiary control which may be achieved by means of changing the set operating points of thermal power plant generation sets, connecting/disconnecting of pumped storage in hydro power station and other standby supplies methods. The tertiary control is usually known as a manual frequency control which applied on the time scale of tens of minutes up to hours after a disturbance. Last control type is the emergency control schemes to manage extreme over/under frequency events. In this control, various load shedding strategies are applied. All of these four controls usually present in modern power systems as shown in Figure (1) below (Bevrani 2009).

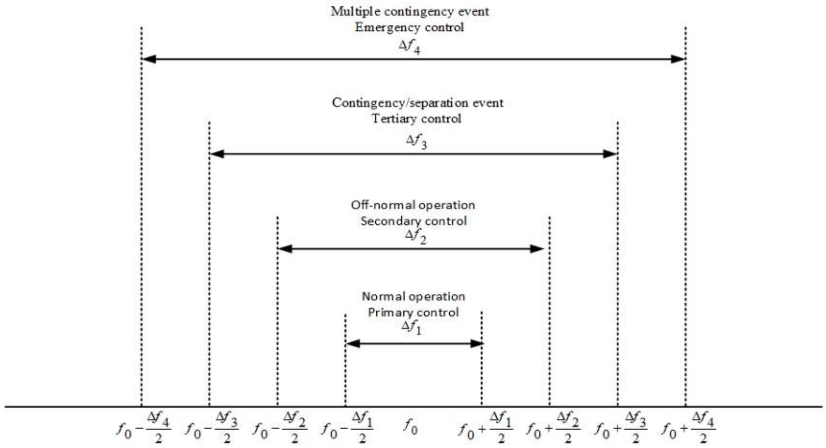


Figure 1. Frequency deviations and associated operation controls.

Where f_0 is the nominal frequency, and $\Delta f_1.\Delta f_2.\Delta f_3$ and Δf_4 show frequency variation ranges corresponding to the different operating conditions based on the accepted frequency operating standards.

1-1 Conventional and intelligent methods for static security assessment:

We obtain voltage monitoring for security assessment by analytically modeling the network and solving load-flow equations many times for all the listed outages, one contingency at a time (Exposito et al,2016). This traditional approach takes a lot of time to complete the calculations. Therefore, the security assessment in most energy management systems uses one or more security predictors to reduce the computational times such as sensitivity matrix, distribution factors, fast decoupled load flows, or performance indicators. Because these analytical methods take a lot of time, so they are not suitable always for real-time applications. Also, they suffer from misclassification or/and false alarm issue that appears when a current contingency is classified as critical. Recently methods based on expert and fuzzy system are used (Swarup and Britto Corthis,2013), and even if they are fast but they lack versatility as many of them are system specific. With the improvements in information processing and learning techniques, methods based on artificial neural network (ANN) become a viable alternative for security assessment applications.

As for frequency monitoring, traditional methods use time domain analysis that employs the Fourier series to estimate power system frequency (Nam et al, 2014), these methods need hardware to provide frequency signals so they lack accuracy most of the times because of this dependence on the hardware. This paper presents an ANN-based method to overcome all these mentioned problems and obtain a fast and accurate tool to monitor system voltage and frequency.

2. Kohonen Self-Organizing Feature Maps

In biological systems, the connections between neurons are excitatory and inhibitory links. In his approach, Kohonen proposed [1982] a fully laterally connected network with distance related strengths of synapses. Neurons close to each other on the grid have a positive (excitatory) connection. Whereas more distant neurons are coupled by negative (inhibitory) connections. And he also proposed a formal model for the construction and functions of topographic maps which he called" topology preserving map" and nowadays known as Kohonen's self-organizing feature map.

2.1 Structure and training algorithm

SOM is simplified model of the feature to the region mapping of the human brain. It is a competitive, self-organizing network which learns from the environment without the aid of the teacher. It has a simple architecture. It consists of a group of geometrically organized neurons in one, two, three or even higher dimensions.

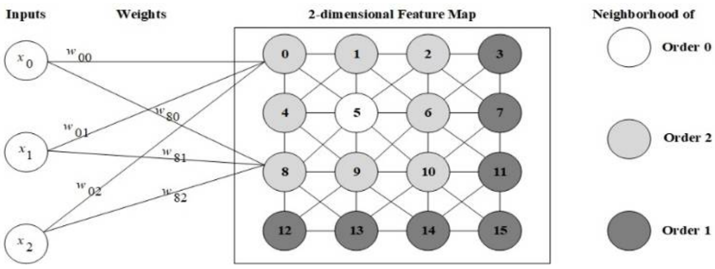


Figure 2. Neural network architecture of the self-organizing feature map.

As shown in figure (2) each neuron has a number of neighboring neurons that effective to each other. Kohonen said that the self-organizing can be obtained with the following neighborhood function that omits the inhibitory connections this function is given by:

$$R(t) = \exp\left(\frac{-\|r(t) - r(t^{*})\|^{k}}{2\sigma(t)^{-\beta}}\right),\ k = 1\ or\ 2 \qquad (1)$$

Where $\sigma(t) = (t)^{-\beta}$, $0 < \beta < 1$ and $r(t)$ are the coordinates of neuron I on the two-dimensional grid, t^{*} is the neuron to be maximally excited and I are the neighboring neurons.

SOMs are unsupervised network so the learning algorithm is given as follows:

1- Initialize the weights from *m* inputs to *n* output units to small random values. Initialize the size of the neighborhood region $R(0)$

2- Present a new input vector *a*.

3- Compute the distance (d_i) between the input and the weight on each output unit *i*:

$$d_i - \sum_{j=1}^{M}\left(a_j(t) - w_{ij}(t)\right)^2 . for\ i - 1,2,\ldots,n \qquad (2)$$

Where $a_j(t)$ is the input to the *j*th input unit at time *t* and $w_{ij}(t)$ is the weight from the *j*th input unit to the *i*th output unit

4- Select the output unit *k* with minimum distance defined by $k = min(d_i)$

5- Update weight to node *k* and its neighbors

$$w_{ij}(t+1) - w_{ij}(t) + \eta\left\{a_j(t) - w_{ij}(t)\right\}\quad for\ i\ R_k(t)\quad and\ j - 1,2,\ldots,m \quad (3)$$

Where $\eta(t)$ is the learning rate parameter $(0 < \eta(t) < 1)$ that decreases with time. $R_k(t)$ gives the neighborhood region around the node *k* at time *t*.

6- Repeat steps 2 through 5 for all input several times.

2.2 Supervised self-organizing maps

Supervised self-organizing map (SSOM) combine incorporate a priori knowledge into the neural network training process (Bayram et al, 2004). We have used the definition introduced by Kohonen and shown in figure (3). A hexagonal neighborhood structure is used to define the map's topological connectivity.

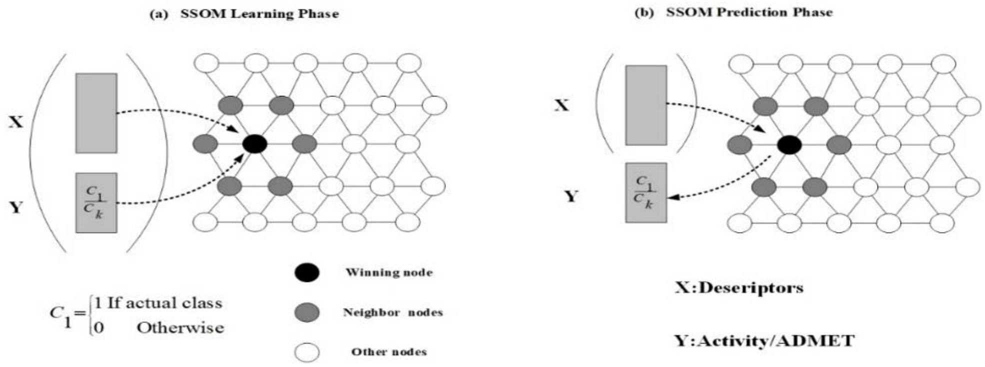


Figure 3. SSOM learning and prediction schemes.

During the learning phase, actual class information of each training compound is attached to its feature vector in binary format. This combined feature vector is fed into the SOM as input to guide the map organization. During the prediction phase, the map that was created during the learning phase is used to relate the features of the compounds to the unknown class information. During training, class information of each compound $Y = [C_1, \dots, C_k]$ is appended to its descriptor vector $X = [x_1, \dots, x_D]$to form the manifold $Z = [X^T Y^T]$. Here, (Y) represent a single column binary valued vector containing bioactivity class information, where only the class index to which the compound belongs is set to 1. This data model allows class information to influence the topological ordering of the map during training, and then the trained map is used for class prediction of unknown compounds.

The use of SSOM so far were in chemical applications and production lines classification (Melssen et al, 2006) or in medical and health applications (Bayram et al, 2004) and (Xiao et al, 2005). In this paper, we will use SSOM as a new technique in power system applications.

2.3 Advantages of SOM and SSOM compared to Feed-forward ANN with back propagation learning algorithm.

There are many kinds of artificial neural networks, but the most famous and widespread one is the feed-forward ANN with back propagation learning algorithm. According to (Goppert and Rosenstiel, 1993), (Malinowski et al., 1995) and (Melssen et al, 2006) we can summarize the main advantages and disadvantages of SOM, SSOM and feed-forward ANN networks in table (1). And as shown in the table we found that SSOM has major advantages over SOM and feed-forward ANNs, because it uses class information that helps to obtain a perfect clustering essential in security assessment application.

Aspect	Multilayer feed-forward	SOM
Learning	Supervised, trained with back propagation algorithm,which requires a known, desired output for each input value.	Unsupervised, learns from the environment without the aid of the teacher.
Convergence	Enhanced convergence but it still depends on training parameters.	Stable convergence, less risk of local minima.
Network size	Performance affected by the size of the hidden layer.	Performance doesn't affect by network size (number of neurons).
Output map	Can construct input-output mapping by learning from examples.	Neighborhood function makes it ideal for classification problems because it helps to give perfect input-output maps.
Robustness and Speed	Enhanced training speed depending on learning technique. Very robust and performance does not affect by noise.	Very fast training (training 20 neurons needs 10 sec) and performance does not affect by noise.

SSOM	Supervised, incorporate a priori knowledge into the neural network training process.	Best convergence with minimum misclassification because of the use of class information.	Performance doesn't affect by network size (number of neurons).	Class information gives a perfect input-output maps with better reproducibility, interpretability and prediction.	Great calculation speed (training 40 neurons less than 10 sec) performance does not affect by noise.

Table 1. Comparison between some ANNs

2. METHODOLOGY AND IMPLEMENTATION

2.2 Power system studied

In our study, we take the Syrian power transmission network (220 kV/50Hz) which consists of 44 buses and 70 lines as follows:

- One slack bus.
- Nine generation buses.
- 34 load buses.

We have added 5 Virtual buses to the 44 buses for calculation purposes and to obtain a 7×7 Kohonen map, where we have 49 neurons so we need a total number of 49 stations.

Full information about this network is found in the appendix at the end of this paper, we studied this network for the following disturbances and contingencies:

- One Normal Operation Condition.
- Fifteen Load Change Cases.
- Nine Single Generation Outages.
- Eight Single Line Outages.
- Two Single Load Outages.

2.3 Data set and construction of SSOM networks

In our study, we formed two SOM networks, one for monitoring voltage and the other for monitoring frequency. The construction and data used in these networks are as follows:

2.3.1 SSOM network to monitor the voltage in power system:

Using active power P and class information Y or apparent power S and class information Y as input data. And because we found that both S and P gives the same results with advantage in calculation speed when taking P as input we decided to choose P as input. The size of the network is (7 by 7) and the total number of neurons is 49, each neuron represents a load bus of the power system in the output map.

2.3.2 SSOM network to monitor the frequency in power system:

Using active power P and class information Y as input data. we deal here with the whole power system so the size of the network is (7 by 7) with a total number of 49 neuron each one of them will represent a bus of the power system in the output map. As for frequency value, we obtain it applying the following equations according to Kusic (2008) after performing the fast-decoupled load-flow technique on the power system:

$$\Delta_{AD} = \frac{(10B_A X_A + 10B_D X_D)\Delta T_L}{(10B_A X_A)} \quad MW \tag{4}$$

Where ΔT_L is the net change in tie-line power flow from initial conditions which is a positive value directed from bus A toward bus D, $B_A . B_D < 0$ are the natural regulation characteristic of bus A and bus D, $X_A . X_D$ are is the generating capacity of bus A and D in megawatts, and Δ_{AD} the magnitude of the disturbance that occurs in bus D.

After calculating Δ_{AD} from equation (4) we can calculate frequency deviation Δ_f from the following equation:

$$\Delta f = \frac{\Delta_{AD}}{10B_A X_A + 10B_D X_D} \quad Hz \tag{5}$$

The frequency value can be calculated as follows:

$$f = f_{base} - \Delta f \quad Hz \tag{6}$$

Where $f_{base} = 50Hz$

2.4 Classes and limits

In our study, we used three classes, safe class assigned with green color in output map, warning class assigned with yellow color in output map and alarm class assigned with red color in output map. To maintain an economic and reliability operation to the power system, we based on the following standards to define voltage, active power, apparent power and frequency limits:

- According to IEEE Standard C50 and VAR-001 and VAR-002 North American Electric Reliability Corporation (NERC), System shall operate successfully at rated kilovolt ampere, and power factor at any voltage range, not more than 5% above or below rated voltage, so the voltage must be between 0.95 - 1.05 pu.
- According to The Union for the Co-ordination of Transmission of Electricity(UCTE) coordinates the interest of transmission system operators in 16 European countries (Chown et al, 2000). So, we chose the following frequency operation bands in our study:

Table 2. Frequency operation bands according to UCTE

Band	Frequency limit [Hz]
Normal band	49.9-50.1
Load change contingency band	49.5-50.5
Single generator contingency band	47.0-51.0
Another credible contingency band	47.0-53.0
Multiple contendingly band	44.8-55.0

3. RESULTS

All the results are obtained using MATLAB (R2013a) programming and specific GUI designed for our study. We will show the input-output map classification for two contingencies:

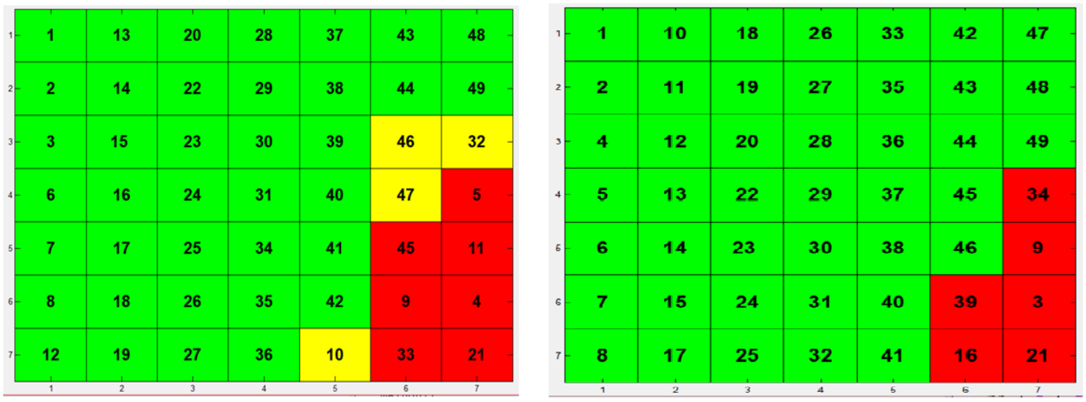
1- Generator outage (station 21).
2- An increase in the load of the station (6) by +35%.

Whereas all the contingencies with buses classification of voltage and frequency SSOM are shown in the appendix at the end of this paper. In the study, we have 36 input vectors (35 contingency and 1 for normal condition) each input vector consists of 86 input unit, so the total number of input units is 3010. We have used 31 vectors (2666 input units) for training the network and 4 vectors (344 input units) for testing the network. The following settings were used to train the network:

- Learning rate value $\eta(t)$ starts at 0.1 and decreases with time to reach 0.001.
- Neighborhood function value $R_k(t)$ starts at 2 and decreases with time to reach 0.
- Number of iteration = 150.
- Size of the network is 7 by 7, so we have 49 neurons.

We found that the overall accuracy of the model as a percentage of correct training units is 95.46% for Voltage SSOM and 100% for Frequency SSOM when generator outage (station 23). Whereas after an increase in the load of the station (6) by +35%, the overall accuracy of the model as a percentage of correct training units is 100% for booth Voltage SSOM and Frequency SSOM.

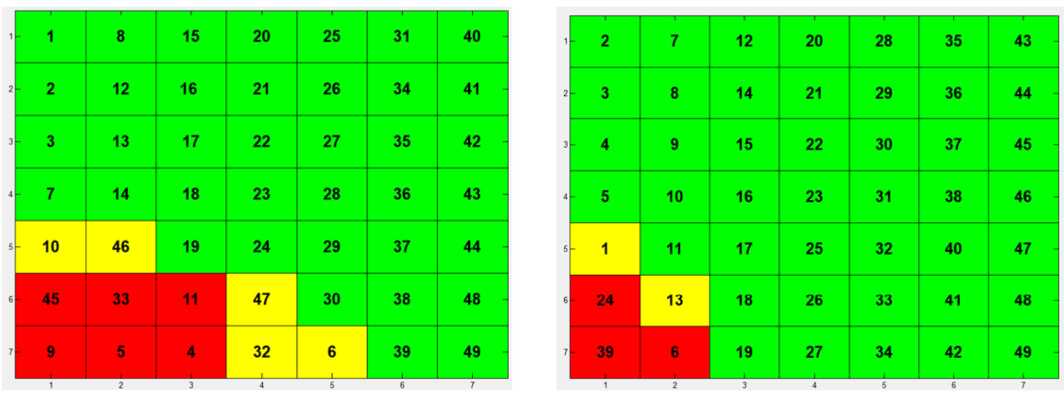
Figure (4) shows input-output map after generator outage (station 21), we found in the voltage SSOM (a) that seven stations: 45,9,33,5,11,4 and 21 were classified in alarm state (red) and four stations: 10,46,47,32 were classified in warning state (yellow), whereas for frequency SSOM (b) we found that six stations 39,16,34,9,3 and 21 were classified in alarm state (red).



(a) **(b)**

Figure 4. Voltage SSOM (a) and Frequency SSOM (b) classification of power network after generator outage (station 21).

Figure (5) shows input-output map after an increase in load of station (6) by +35%, we found in the voltage SSOM (a) that six stations: 45,9,33,5,11 and 4 were classified in alarm state (red) and five stations: 10,46,47,32 and 6 were classified in warning state (yellow), whereas for frequency SSOM (b) we found that three stations 24,39 and 6 were classified in alarm state (red) and two stations:1 and 13 were classified in warning state (yellow).



(a) **(b)**

Figure 5. Voltage SSOM (a) and Frequency SSOM (b) classification of power network after an increase in the load of the station (6) by +35%.

In figure (6) we can see the calculation speed of SSOM compared with the traditional load flow (Fast-decoupled load-flow).

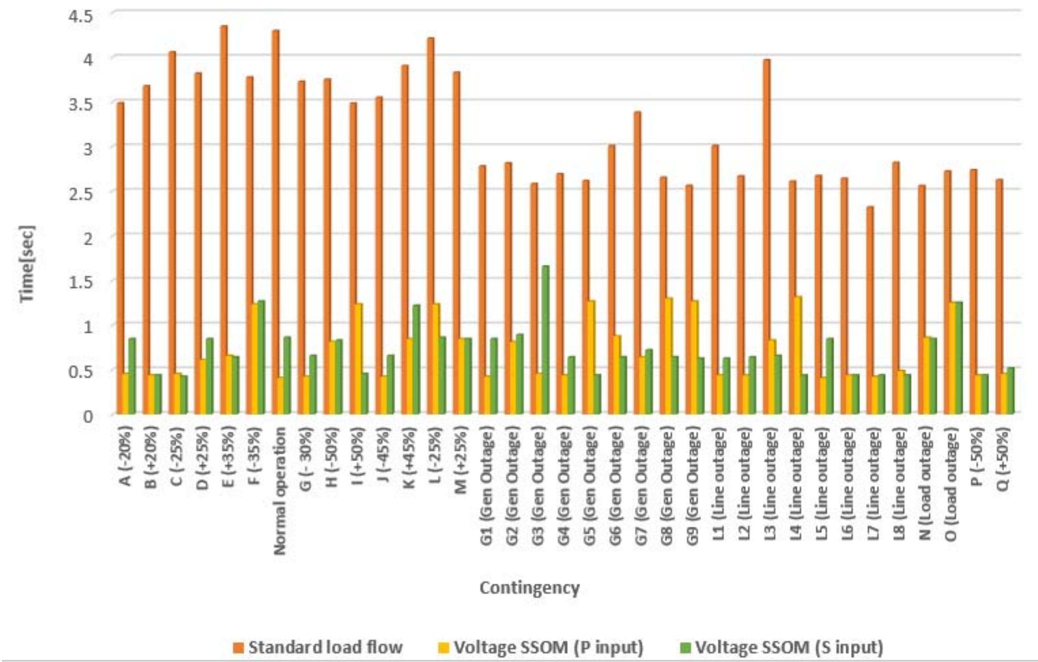


Figure 6. Average calculation times for SSOM networks compared to standard load flow method.

figure (7) shows the calculation speed of frequency SSOM, where we see that the maximum time needed is Three-level DFT and Prony 0.4 to 0.9 sec except for one contingency where the time reaches 1.3 sec.

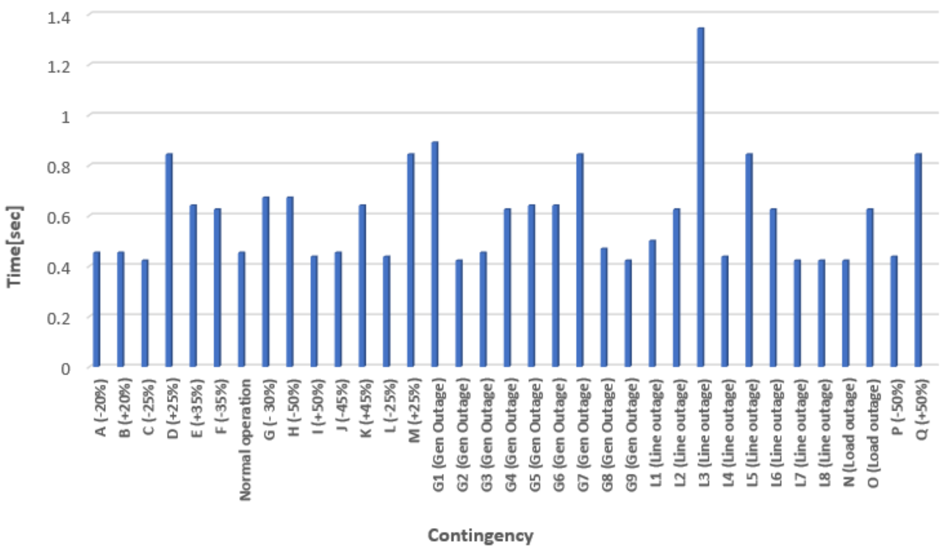


Figure 7. Average calculation times for frequency SSOM network.

figure (8) shows the calculation speed to estimate frequency using traditional methods such as: Three-Level Discrete Fourier Transform (Three-level DFT) and Prony method as descriped by (Nam et al, 2014), Where the system simulation was processed using Matlab, and the sampling frequency was set to 1920 Hz (32 samples per cycle in a 60-Hz system). We can see that both three-level DFT and Prony converges to the final reference frequency takes 1.01 sec.

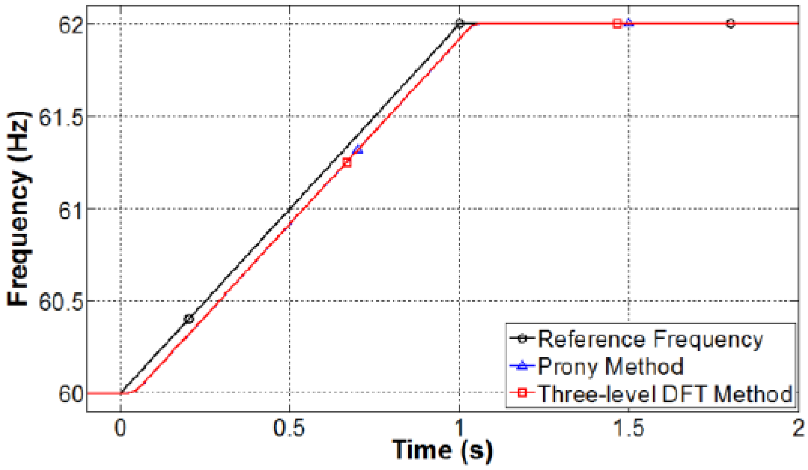


Figure 8. calculation speed using Three-level DFT and Prony frequency estimatetion methods.

4. Discussion

As shown in sections (3), input-output maps provide clustering of buses according to the state of the bus with the number of the station associated with this bus, providing a simple information to the system operator to take a corrective action to restore the system to a secure state. We found that the voltage SSOM gives full classification of power system with calculation speed 2 -3 times faster (figure 6) than the traditional load flow based methods, and the frequency SSOM classifies the system with calculation speed 1.12% to 2.525% faster (figures 7 and 8) than the traditional based methods such as Three-level DFT and Prony.

5. Conclusion

This paper proposed a method based on supervised self-organizing maps for clustering a power system. Which is a very useful technique in static security assessment and voltage stability control. By forming these clusters we reduce the size of power network so computational efficiency is considerably increased. The Kohonen-NN used unsupervised training then we added a patch to make this method supervised, the thing that enhanced the construction of input-output maps. The results obtained in various loads and contingencies showed that this method can be used to practical systems to give useful information about voltage and frequency stability to the system operator.

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Appendix

Table 3. Buses information (P in MW and Q in MVar)

Station	PG	QG	PL	QL	**Station**	PG	QG	PL	QL
1	0	0	113.68	68.21	**26**	0	0	157.41	94.44
2	0	0	167.12	100.27	**27**	0	0	84.05	50.43
3	0	0	88.42	54.05	**28**	0	0	170.52	102.31
4	0	0	120	72.29	**29**	0	0	0	0
5	0	0	156.43	93.86	**30**	0	0	0	0
6	0	0	89.39	53.63	**31**	0	0	202.10	121.26
7	0	0	151.58	90.95	**32**	0	0	194.33	116.60
8	0	0	113.19	67.92	**33**	0	0	137.0	82.20
9	0	0	106.88	64.13	**34**	0	0	120.48	72.29
10	0	0	169.07	101.44	**35**	0	0	171.98	103.19
11	0	0	120.48	72.29	**36**	0	0	0	0
12	0	0	44.7	26.82	**37**	0	0	170.52	102.31
13	0	0	141.86	85.12	**38**	0	0	170.04	102.02
14	660	408.54	34.59	20.76	**39**	0	0	62.19	37.31
15	150	92.85	38.38	23.03	**40**	0	0	0	0
16	710	439.49	89.39	53.63	**41**	0	0	116.11	69.67
17	600	371.4	83.56	50.14	**42**	0	0	160.32	96.95
18	90	55.71	40.81	24.49	**43**	0	0	85.50	51.30
19	300	185.7	58.30	34.98	**44**	0	0	200	67.63
20	600	37104	77.73	46.64	**45**	0	0	141.86	85.12
21	450	278.55	58.50	51.30	**46**	0	0	184.61	110.76
22	660	408.54	39.84	23.90	**47**	0	0	162.75	97.65
23	0	0	142.83	85.12	**48**	0	0	0	0
24	0	0	48.58	29.15	**49**	0	0	0	0
25	0	0	0	0	**-**	-	-	-	-

Table 4. lines information (R and X in Ohm)

N	From	To	R	X	N	From	To	R	X
1	1	41	13.1	53.36	**36**	31	12	4.61	18.79
2	1	2	11.17	45.53	**37**	32	10	0.1	0.43
3	1	36	2.54	10.34	**38**	33	4	0.94	3.82
4	2	18	2.42	9.87	**39**	33	5	1.33	5.41
5	7	16	1.42	5.81	**40**	34	3	0.312	1.273
6	8	48	14.52	59.19	**41**	35	31	3.9	15.92
7	8	14	1.4	5.76	**42**	35	21	3.21	13.08
8	8	37	1.67	6.84	**43**	38	17	1.145	4.665
9	8	48	15.2	61.92	**45**	38	19	2.34	9.55
10	8	16	2	13.86	**46**	38	20	8.28	33.75
11	8	22	0.39	1.61	**47**	39	30	0.566	2.316
12	8	30	10.54	42.98	**48**	41	15	10.6	43.3
13	10	44	10.95	43.84	**49**	41	2	10.15	41.39
14	10	42	1.07	4.39	**50**	41	6	6.1	24.83
15	10	38	2.18	8.89	**51**	42	38	2.7	10.98
16	10	4	0.76	3.18	**52**	42	26	0.615	2.515
17	15	6	3.46	27.7	**53**	43	39	1.3	5.31
18	16	27	1.01	4.10	**54**	43	30	4.3	17.51
19	16	34	3.86	15.72	**55**	43	13	0.76	3.18
20	17	26	7.8	31.84	**56**	44	7	6.125	24.96
21	17	28	1.95	7.95	**57**	44	37	1.64	6.68
22	17	9	8.75	35.66	**58**	44	22	1.49	6.08
23	18	11	6.72	27.38	**59**	45	9	3.75	15.28
24	19	33	4.37	17.83	**60**	45	26	4.37	17.83
25	21	3	5.9	24.03	**61**	46	12	7.8	31.84
26	24	39	7.55	30.78	**62**	47	5	0.478	1.942
27	24	12	1.62	6.63	**63**	48	43	12	49
28	25	18	7.8	31.84	**64**	48	24	6.7	27.32
29	26	42	1.33	5.41	**65**	48	1	1.348	5.481
30	26	47	1.5	6.11	**66**	48	36	1.72	7
31	26	29	0.38	1.59	**67**	7	Lebanon	5	20.37
32	30	23	1.36	5.57	**68**	15	Iraq	3.12	12.73
33	30	13	1.6	6.52	**69**	39	Turkey	4.1	16.55
34	31	46	1.23	5.06	**70**	45	Jordan	4.2	17.19
35	31	13	0.76	3.18	**-**	-	-	-	-

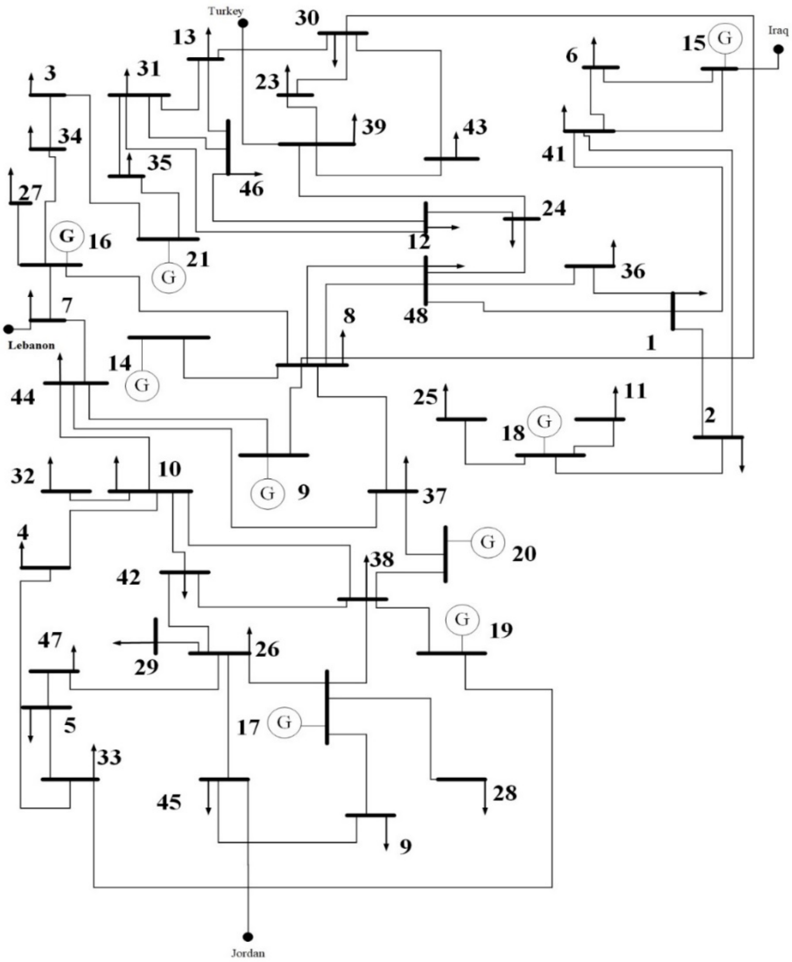

Figure 9. Syrian power transfer system.

Table 5. Voltage SSOM buses classification for all contingencies.

Cont	Bus class		Cont	Bus class	
	Warning	Alarm		Warning	Alarm
A(-20%)	10-46-47-32-1	45-9-33-5-11-4	**G3 out**	10-46-47-32	45-9-33-5-11-4-16
B(+20%)	10-46-47-32-2	45-9-33-5-11-4	**G4 out**	46	10-45-9-33-47-5-32-11-4-17
C(-25%)	10-46-47-32-3	45-9-33-5-11-4	**G5 out**	10-46-47-32	45-9-33-5-11-4-18
D(+25%)	10-46-47-32-4	45-9-33-5-11	**G6 out**	10-46-47	45-9-33-5-32-11-4-19
E(+35%)	10-46-33-47-5-32-4	45-9-11	**G7 out**	10-46-47-32	45-9-33-5-11-4-20
F(-35%)	10-46-47-32-6	45-9-33-5-11-4	**G8 out**	10-46-47-32	45-9-33-5-11-4-21
G(- 30%)	10-46-47-32-7	45-9-33-5-11-4	**G9 out**	10-46-47-32	45-9-33-5-11-4-22
H(-50%)	10-46-47-32-8	45-9-33-5-11-4	**L1 out**	10-46-47-32	45-9-33-5-11-4-23
I(+50%)	10-46-47-32	45-9-33-5-11-4	**L2 out**	10-46-47-32	24-45-9-33-5-11-4
J(-45%)	10-46-33-47-32-4	45-9-5-11	**L3 out**	10-46-47-32	1-45-9-33-5-11-4
K(+45%)	10-46-47-32	45-9-33-5-11-4	**L4 out**	10-35-46-33-47-32	45-34-9-5-11-4
L(-25%)	10-46-47-32-12	45-9-33-5-11-4	**L5 out**	10-46-47-32	45-9-33-5-27-11-4
M(+25%)	10-46-47-32-13	45-9-33-5-11-4	**L6 out**	10-35-46-33-47-32	45-9-5-28-11-4
P(-50%)	10-46-33-47-5-32-4	45-9-11	**L7 out**	10-46-47-32	45-9-33-5-11-4
Q(+50%)	10-35-46-47-32-34	45-9-33-5-11-4	**L8 out**	10-35-46-47-5-32-4	45-9-33-11
G1 out	10-46-47-32	45-9-33-5-11-4-14	**N load out**	10-47-32	45-31-9-33-5-11-4
G2 out	10-46-47-32	45-9-33-5-11-4-15	**O load out**	35-46-33-47-5-4	45-9-32-11

Table 6. Frequency SSOM buses classification for all contingencies.

Cont	Bus class		Cont	Bus class	
	Warning	Alarm		Warning	Alarm
A(-20%)	1-13	24-39	**G3 out**	-	24-7-39-34-3-21-16-22-12-13
B(+20%)	2	34-3-21	**G4 out**	-	24-16-34-37-9-20-21-17-3-22-12-13
C(-25%)	3-21	37-22-4	**G5 out**	-	2-16-9-18-17
D(+25%)	21	37-22-4	**G6 out**	20	24-39-16-34-37-17-9-19-21-3-22
E(+35%)	16	24-39-34-37-19-21-5-22	**G7 out**	-	13-3-22-12-21-9-20-34-16-39-24
F(-35%)	1-13	24-39-6	**G8 out**	-	39-16-34-9-3-21
G(- 30%)	24-39-16-11	7-34-21-22	**G9 out**	-	24-39-16-34-9-22-21-3-13-12
H(-50%)	-	8-24-39-34-22	**L1 out**	-	-
I(+50%)	-	24-39-34-37-9-21-17-22	**L2 out**	-	24-39-12
J(-45%)	19-3-13	10-24-39-16-34-37-21-22	**L3 out**	34-9	1-24-39-21-12-13
K(+45%)	43	24-1-39-2-11-18-12-13	**L4 out**	-	24-39-16-34-9-3-21-22-13
L(-25%)	1	12	**L5 out**	-	27-16-34-9-21-22
M(+25%)	-	13-39	**L6 out**	-	17-3-47-28-12-21-34-16
P(-50%)	-	4-5-33-22	**L7 out**	9-34-5	43-24-1-41-11-39-2-13-12-21
Q(+50%)	-	16-21-3-34	**L8 out**	43-38-12	44-24-7-33-9-47-5-4-22-21-19-17-34-16-39
G1 out	-	24-14-39-16-34-3-21-22-12-13	**N load out**	-	13-12-31-39
G2 out	-	24-1-41-6-12-15	**O load out**	-	10-44-32-9-13-22-21-24-34-16-39