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Voltage Problem Location Classification Using Performance of Least Squares Support Vector Machine LS-SVM and Learning Vector Quantization LVQ

Khaled Abduesslam. M, Mohammed Ali, Basher H Alsdai, Muhammad Nizam, Inayati

Abstract**—**This paper presents the voltage problem location classification using performance of Least Squares Support Vector Machine (LS-SVM) and Learning Vector Quantization (LVQ) in electrical power system for proper voltage problem location implemented by IEEE 39 bus New- England. The data was collected from the time domain simulation by using Power System Analysis Toolbox (PSAT). Outputs from simulation data such as voltage, phase angle, real power and reactive power were taken as input to estimate voltage stability at particular buses based on Power Transfer Stability Index (PTSI).The simulation data was carried out on the IEEE 39 bus test system by considering load bus increased on the system. To verify of the proposed LS-SVM its performance was compared to Learning Vector Quantization (LVQ). The results showed that LS-SVM is faster and better as compared to LVQ. The results also demonstrated that the LS-SVM was estimated by 0% misclassification whereas LVQ had 7.69% misclassification.

Keywords**—**IEEE 39 bus, Least Squares Support Vector Machine, Learning Vector Quantization, Voltage Collapse.

I. Introduction

In recent years, voltage instability which is responsible for several major network collapses have been reported in many countries [3]. Many existing methods of power quality location problem have been found not effective, hence causing the errors in the diagnosis and identification [4] and [5]. If such disturbances are not mitigated they can lead to failures or malfunctions of various sensitive loads in power systems and may be costly. In order to improve the electrical power quality the sources of power disturbances should be known and controlled by detecting and classifying of different power system disturbances.

However the accurate fault location is a very challenging task, for the transmission line protection a more accurate location results in the minimization of the amount of time spent by the repair crews in searching for the fault.

The purpose of studying basic idea for the SVM and LVQ was to determine the structure of the classifier by minimizing the bounds of the training error and generalization error [1], [2].

The power transfer stability index (PTSI) was calculated by providing information of thevenin voltage, phase angle of thevenin and impedance and totally power load. The value of PTSI was between 0 and 1, when power transfer stability index value reached 1 it meant that volte happened. [6].

Therefore, this study focuses on the classified with the Least Squares using Support Vector Machine (LS-SVM).The important structure of the classifier is to minimize the bounds of the training error and grangerization error, and then compare with the Learning Vector Quantization (LVQ), to verify the effectiveness of the proposed method LVQ Neural Intelligent uses.

II. Power Transfer Stability Index

The power transfer stability index (PTSI) is calculated by known information for voltage, phase angle, impedance at load bus and total load power [2].

$$PTSI = \frac{2 S_L Z_{Theve} (1 + \cos(\beta - \alpha))}{E^2_{Theve}} \tag{1}$$

The S_L is load power at a bus, α is phase angle of load bus impedance, Z_{Thev} is thevenin impedance, β is phase angle of at thevenin impedance, E_{Thev} is thevenin Voltage.

III. Least Squares Support Vector Machine

Least Square Support Vector Machine (LS-SVM) is a reformulation of the standard SVM, the reformulation leads to solving a set of linear equations which is easier to solve than SVM quadratic equations. The reformulation does not result in SVM losing any of its advantage. LS-SVM map input vectors to a higher dimensional space where a maximum separating hyper plane is constructed.

LS-SVM is a reformulation of the standard SVM. Its mathematical formula is described in this section. Given the training data set, $\{x_k, y_k\}_{k=1}^{N}$ where $x_k \in R^n$ represent, k-th input pattern and $y_k \in R$ is the k-th output pattern, the LS-SVM aims at constructing a classifier of the form,

K.Abduesslam, M.–MSc, is with the Mechanical Engineering, Sebelas Maret University (UNS), Central Java, Indonesia (2014) (e-mail: Khaled.abdoo20@yahoo.com).

M. Ali Khalifa and B. H. Alsdai are currently doing thesis work toward the MSc degree in Sebelas Maret University, Central Java, Indonesia (e-mail: besdai@yahoo.com.)

M. Nizam. M. T. ph., D MIEEE., IPM. is Member of University Sensate / Head of control unit UNS Ex. Power System. Power Quality. Energy Management System. (Phone +62271632; +6227164228. Mobile +6281567900856. e-mail: Nizam_kh@ieee.org).

Inayati ST., MT., PhD, is with the Chemical Engineering Department, Faculty of Engineering, Sebelas Maret University, Surakarta, Indonesia (Phone: +62271632112 (office) 6282138248908 (mobil); e-mail: inayati@fi.uns.ac.id).

$$y(x) = \text{sign}\left[\sum_{k=1}^{N}\alpha_k y_k \psi(x, x_k) + b\right] \tag{2}$$

where α_k is positive real constant and b is a real constant. $\psi(x,x_{-k}) = \exp\left\{\frac{-\|x - x_k\|^2}{2\sigma^2}\right\}$ is the RBF kernel which is considered in this work.

The least squares version to the SVM classifier is done by formulating the classification problem as,

$$\min_{w,b,e} J(w,b,e) = \frac{1}{2}w^T w + \gamma \frac{1}{2}\sum_{k=1}^{N} e^2{}_k \tag{3}$$

Subject to equality constraints,

$$y_k\,[w^T\varphi(x_k) + b] = 1 - e_k,\ k = 1,\ldots,N \tag{4}$$

where$\varphi(x_k)$ is a nonlinear function which maps the input space into a higher dimensional space. By using the Mercer's Theorem, this function is related to $\psi(x, x_k)$ as follows,

$$\varphi(x)^T\varphi(x_k) = \psi(x, x_k) \tag{5}$$

Equation (1) lead to Karush-Kuhn-Tucker systems and can be written as the solution to the following set of linear equations,

$$\begin{bmatrix} 0 & -Y^T \\ Y & ZZ^T + \gamma^{-1}Y \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{1} \end{bmatrix} \tag{6}$$

where:
$Z = [\varphi(x_1)^T\ y_1; \ldots; \varphi(x_N)^T y_N]$.
$Y = [y_1; \ldots; y_N]$.
$\vec{1} = [1; \ldots; 1]$.
$E = [e_1; \ldots; e_N]$.
$\alpha = [\alpha_1; \ldots; \alpha_N]$.

Mercer's Theorem can be applied again to the matrix $\Omega_{-kl}= ZZ^T$ where,

$$\Omega_{kl} = y_k y_l \varphi(x_k)^T\varphi(x_l) = y_k y_l \psi(x_k, x_l) \tag{7}$$

Hence, the solution to the classifier as given in (2) can be found by solving the linear set of (6) and (7) instead of using quadratic programming for solving the equation as is the case with SVM. The LS-SVM network developed in this work uses the LS-SVM Matlab Toolbox in which the training of LS-SVM is based on the iterative, solver conjugate gradient algorithm.

IV. Performance Evaluation

Performance of the developed LS-SVM network can be measured by calculating the error of the actual and expected test data. First, error is defined as,

$$\text{Error, } E_n = |\text{Desired Output, } DO_n - \text{Actual Output, } AO_n \tag{8}$$

where, n is the test data number. The desired output is the known output data used for testing the neural network. Meanwhile, the actual output (AO) is the output obtained from testing on the trained network.

From (5), the mean square error (MSE) can be obtained as:

$$MSE = \frac{1}{n}\sum_{i-1}^{n}(xi - yi)^2 \tag{9}$$

where n is the total number of test data. The percentage classification error (CE) is given by,

$$CE\% = \frac{\text{no. of test data } \textit{misclassification}}{N} \times 100 \tag{10}$$

Equation (10) can be solved by using a time domain simulation program through step-by-step integration in order to produce time response of all state variables.

V. Learning Vector Quantization (LVQ)

LVQ classification tool is invented by Teuvo Kohonen. There are three type of LVQ such as: LVQ1, LVQ2, LVQ3. [8] The proposed model using LVQ1, the algorithm of LVQ1 as follows:

X : training vector ($x_1, \ldots, x_i, \ldots, x_n$).
T : correct category or class for the training vector.
W_j : weight vector for jth output unit ($w_{1j}, \ldots w_{ij}, \ldots W_{nj}$).
C_j : category or class represented by jth output unit.
||X – Wj|| : Euclidean distance between input vector and (weight vector for) jht output unit.

Step 0. Initialize reference vector (several strategies are discussed shortly), Initialize learning rate, α (0).
Step 1. While stopping condition is false, do Steps 2-6.
Step 2. For each training input vector x, do Steps 3-4.
Step 3. Find J so that $\|X - Wj\|$ is a minimum.
Step 4. Update w_j as follows:
if T - C_j, then
$wj(new) = w_j(old) + \alpha\,[x - w_j(old)]$; If $T \neq C_J$, then
$w_J(new) = w_J(old) - \alpha\,[x - w_J(old)]$.
Step 5. Reduce learning rate.
Step 6. Test stopping condition: The condition may specify a fixed number of iterations (i.e., execution of Step 1), or the learning rate reaching a sufficiently Small value.

VI. Method

The dynamic simulation of voltage collapse study was carried out using the Power System Analysis Toolbox (PSAT) [7] software program. The procedures in this study were described as following:

1. Generator, Transmission Line and Load data were input in the test system. Afterwards, the load flow was run for the base case.
2. Training and testing data were generated for the LS-SVM, by doing Simulations considering (a) increase one load bus

at 2% MVA until the system collapse, the voltage, phase angle, real and reactive powers were measured and calculated PTSI at all the load buses.

3. A data base was created for the input vector in the form of [P_L, Q_L, V_L, θ] where P_L, Q_L and V_L are the load real, reactive power, the voltage magnitude at a load bus, respectively. h is the voltage phase angle. Therefore, the corresponding input vector and class for LVQ and LS-SVM classification is 1, 2.
4. A set of data namely Voltage (V), phase angle (θ), Real Power (P) and Reactive Power (Q) were input at each bus and every contingency was taken from simulation results of LS-SVM and LVQ.

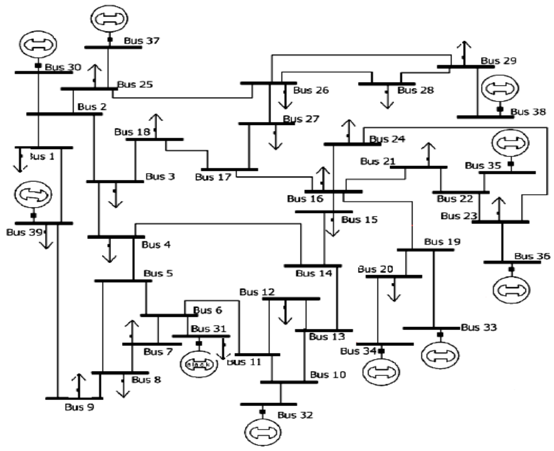

Fig. 1 Single line diagram of IEEE-39 bus New-England system

The use of LS-SVM was proposed to find performance of the method of Least Squares Support Vector Machine (LS-SVM) and Learning Vector Quantization (LVQ) for electrical power system by means of classifying the system into either stable or unstable states by considering load increase as the contingency applied to the system. Time domain simulations was first carried out to generate training data for the LS-SVM and to determine the transient stability state of a power system by visualizing the change due to increase or decrease of voltage. The LS-SVM was then compared with the Learning Vector Quantization LVQ to evaluate its effectiveness in determining voltage fault problems.

VII. Results and Discussions

The algorithm for the LVQ net was to find vector. X was training vector of voltage, phase angle, real and reactive power. The class one was unstable load bus and two was stabile load bus. It was determined which one bus was stable and unstable at all load buses system which is shown in the Table I.

TABLE I
ALL ACTUAL DATA AND OUTPUT LVQ CLASSIFICATION

Test Data	Actual Class	LVQ
1	2	2
2	2	2
3	2	2
4	2	2
5	2	2
6	2	2
7	2	2
8	2	2
9	2	2
10	2	2
11	2	2
12	2	2
13	2	2
14	2	2
15	2	1
16	1	1
17	1	1
18	2	1
19	1	1
20	1	1
21	1	1
22	1	1
23	1	1
24	1	1
25	2	2
26	1	1
27	1	1
28	1	1
29	1	1
30	2	2
31	2	2
32	2	2
33	1	1
34	1	1
35	1	1
36	1	2
37	2	2
38	1	1
39	2	2

TABLE II
ALL ACTUAL DATA AND OUTPUT LS-SVM CLASSIFICATION

Test data	Actual Class	LS-SVM
1	2	2
2	2	2
3	2	2
4	2	2
5	2	2
6	2	2
7	2	2
8	2	2
9	2	2
10	2	2
11	2	2
12	2	2
13	2	2
14	2	2
15	2	2
16	1	1
17	1	1
18	2	2
19	1	1
20	1	1
21	1	1
22	1	1
23	1	1
24	1	1
25	2	2
26	1	1
27	1	1
28	1	1
29	1	1
30	2	2
31	2	2
32	2	2
33	1	1
34	1	1
35	1	1
36	1	1
37	2	2
38	1	1
39	2	2

TABLE III
COMPARISON OF PERFORMANCE LS-SVM CLASSIFICATION AND LVQ CLASSIFICATION

Method	Parameter comparison	
	Training time (second)	MSE
LS-SVM Classification	0.003	0
LVQ Classification	31.985	0.076

Results showed that the LS-SVM gave better performance than the Learning Vector Quantization LVQ in terms of stability and instability classification. Another advantage of LS-SVM was that the training time was significantly less as compared to LVQ. The LS-SVM succeeded for the classification of 39 testing data 100%, whereas LVQ succeeded only 92.31%.

VIII. CONCLUSION

It can be concluded that LS-SVM is better for the classification of solving voltage problem of power system than LVQ method. The study recommend to electrical companies and suppliers use the LS- SVM instead of LVQ method for fault location since LS-SVM give more promising and accurate result in short time for problem identification. In addition, further study is needed on contingency of a sudden damage in the electrical grid and the speed determined location collapse to predict the increases in load power at substations by calculating support vector machine.

APPENDIX

TABLE IV
CLASSIFICATION OF ALL BUSES ACTUAL CLOSES

No	P_L	Q_L	V	θ	Actual Closes
1	0.976	0.442	1.003	-1079.58	2
2	0	0	1.059	-1079.942	2
3	3.22	0.024	1.053	-1080.055	2
4	5	1.84	1.033	-1080.047	2
5	0	0	1.031	-1079.979	2
6	0	0	1.036	-1079.97	2
7	2.338	0.84	1.013	-1079.967	2
8	5.22	1.77	1.005	-1079.955	2
9	0.065	-0.67	0.995	-1079.583	2
10	0	0	1.058	-1079.985	2
11	0	0	1.05	-1079.981	2
12	0.085	0.88	1.039	-1079.994	2
13	0	0	1.054	-1080.004	2
14	0	0	1.049	-1080.05	2
15	3.2	1.53	1.066	-1080.155	2
16	3.29	0.323	1.09	-1080.173	1
17	0	0	1.08	-1080.15	1
18	1.58	0.3	1.067	-1080.122	2
19	0	0	1.145	-1080.188	1
20	6.8	1.03	1.098	-1080.237	1
21	2.74	1.15	1.091	-1080.163	1
22	0	0	1.106	-1080.120	1
23	2.475	0.846	1.096	-1080.129	1
24	3.086	-0.922	1.095	-1080.181	1
25	2.24	0.47	1.052	-1079.991	2
26	1.39	0.17	1.096	-1080.142	1
27	2.81	0.755	1.083	-1080.165	1
28	2.06	0.27	1.134	-1080.187	1
29	2.835	0.269	1.145	-1080.174	1
30	0	0	1.052	-1079.876	2
31	0.092	0.046	1.047	-1079.856	2
32	0	0	1.047	-1079.909	2
33	0	0	1.094	-1080.147	1
34	0	0	1.138	-1080.194	1
35	0	0	1.107	-1080.061	1
36	0	0	1.087	-1080.054	1
37	0	0	1.059	-1079.923	2
38	0	0	1.137	-1080.125	1
39	11.15	2.525	1.026	-1079.332	2

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Khaled Abduesslam M. was born in 09-07-1983, Tekarkeba ,libya. Graduated master degree from Sebelas Maret University (UNS), Central Java, Indonesia. (2014), His research interest includes Power System Analysis, Power Electronics ,Power Quality, Control Systems, and Renewable Energy.
Email:Khaled.abdoo20@yahoo.com

Mohammed Ali Khalifa was born in 13-06-1988, Sebha ,libya.He is currently doing thesis research toward the MSc degree in SebelasMaret University, Central Java, Indonesia. His research interest includes Power System Analysis, Power Electronics ,Power Quality,Control Systems, and Renewable Energy.
Email: talal_feb2011@yahoo.com

Basher H Alsdai was born in 19-11-1985, Zliten, Libya. He is currently doing research wotktoward the MSc degree in SebelasMaret University, Central Java, Indonesia. His research interest includes control systems, renewable energy, and heat transfer, thermodynamic.
Email: besdai@yahoo.com

Prof. Muhammad Nizam. M. T. PhD, MIEEE., IPM. Member of University Sensate / Head of control unit UNS Ex. Power System. Power Quality. Energy Management System. Phone +62271632; +6227164228. Mobile-phone: 081567900856.
Email: Nizam_kh@ieee.org

Inayati, ST., MT., PhD.Chemical Engineering Department, Faculty of Engineering, Sebelas Maret University, Surakarta, Indonesia.Telp: +62271632112 (office) +62274375213 (home) +6282138248908 (mobile) (E-mail: inayati@fi.uns.ac.id)