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Synchrophasor Assisted Fault Diagnosis Using Support Vector Machine

Paavani P*, Singh S N* and Srivastava S C*

This paper presents a Support Vector Machine (SVM) based fault detection, classification and location using synchrophasor measurements obtained from the optimally placed Phasor Measurement Units (PMUs) for ensuring fault observability. An Integer Linear Programming (ILP) based PMU placement method is proposed, considering the minimization of installation cost as objective with line observability as its constraint. The breaker and half bus-bars scheme is considered at one of the substations to show its impact on the Optimal PMUs Placement (OPP). After the OPP, a SVM based post-fault studies are carried out using the synchrophasor measurements, available from the PMUs. Three types of SVM-Classifiers (SVM-C) are used for the fault detection, faulted line identification and the fault classification. Further, fault location is carried out using Support Vector Regressor (SVR) in which four SVMs are utilized, one for each fault type. The same classification and regression is carried out using Radial Basis Neural Networks (RBFNNs) and the results obtained from SVM are compared. The performance of the proposed method is studied on WSCC-9 bus system with and without consideration of the breaker and half bus-bar scheme and on New England (NE)-39 bus system.

Keywords: *Phasor measurement unit (PMU), Binary integer programming, Support vector machine, Fault diagnosis, Optimal PMUs placement.*

1.0 INTRODUCTION

A power system network is subjected to the various types of faults resulting in excessive current flow in the network and, sometimes, this leads to instability of the system. Thus, an accurate fault diagnosis technique is important in improving the power system security and reliability. The overall fault diagnosis problem involves: *fault detection* whether fault has taken place, *fault classification* to find out whether the fault is 3-phase, line-to-line, single line-to-ground, double line-to-ground fault, *faulted line identification* and *fault location estimation*. Recently, synchrophasor based Wide Area Monitoring and Control Systems (WAMCS) are increasingly being deployed in the power utility networks to enhance real time monitoring and control of the system. This supplements the conventional Supervisory Control and Data Acquisition (SCADA) system, and is capable of providing synchronized voltage and current phasor measurements. These phasors are generated at PMU located in the field utilizing Global Positioning System (GPS) for the time synchronization.

With the availability of voltage and current phasors at a faster rate, accurate and fast techniques for the fault diagnosis can be evolved. However, PMU placement on each bus of the transmission system is not practically feasible due to cost factor. Hence a suitable methodology is needed to determine the optimal locations of PMUs for making system observable for fault location view point in a transmission network. Since, a rigorous formulation of the optimal placement becomes

*Department of Electrical Engineering, IIT, Kanpur, India. E-mail: ppavani@iitk.acin, snsingh@iitk.ac.in, scs@iitk.ac.

very difficult and it is time consuming to search for the global optimal solution, a systematic procedure which presents nearly optimal solution is usually desired to develop the PMUs placement strategy.

In [12], the OPP has been carried out using ILP, which ensures the bus observability of the complete system. An exhaustive search based approach has been proposed in [4] to determine the minimum number and optimal placement of PMUs for state estimation, considering single branch outages. The ILP based PMU placement ensuring numerical observability and the numerical observability involves calculation of measurement Jacobian which reflects system configuration and measurement set has been proposed in [6]. In [13], the PMUs placement based on topological observability has been proposed out using simulated annealing. Multi-staging of PMUs placement using integer linear programming has been carried out in [7]. The optimal PMUs placement has been done using spanning trees of a power system for complete system observability and the optimal number has been reduced as compared to complete observability by using depth of unobservabiltiy in [9].

A linear programming based approach has been proposed in [10] that maintains system observability under intact and single network outage. The recent developments in the PMU based wide area protection and its key role has been comprehensively surveyed in [11]. The present and possible future applications such as state estimation, stability studies and wide area protection, etc. of the phasor measurement units have been well documented in [14,15,2]. The PMUs placement based on heuristic approach to make system fault location observable has been carried out and the travelling wave theory has been used for finding the fault location in [5]. A new adaptive fault location technique based on PMU for transmission line is presented in [16] where, voltage and current phasors are obtained through PMU placed on both ends of the line. A SVM based fault diagnosis is carried out in [8] where, 5 cycles of during fault phasor values of voltages and currents during fault given as input feature vector to the SVM are not time stamped.

This paper proposes a topological based approach for the optimal PMUs placement to make the system completely observable for transmission network fault diagnosis. An ILP based PMU placement has been considered, making system complete line observable which can readily detect and locate the fault in a transmission line accurately. The impact of breaker and half busbars scheme on the proposed OPP method has also been investigated. A SVM based fault diagnosis approach is proposed using the synchrophasor measurements obtained from the optimally placed PMUs. The Synchrophasor data is collected from PMUs during fault condition and post fault one cycle each given as input feature to the SVM. The effectiveness of the proposed method is tested on WSCC-9 bus system with and without considering breaker and half scheme and on NE-39 bus system.

2.0 BREAKER AND HALF SCHEME: A REVIEW

The bus-bar schemes in transmission substations are generally configured in ring bus or more often breaker and half bus-bars scheme. In a breaker and half scheme, for every 2 circuits, there are 3 circuit breakers (B), thus, each circuit sharing a common breaker as shown in Figure 1. Any breaker can be removed for maintenance without affecting the service on the corresponding existing feeder transformer (T/f), and a fault on either bus can be isolated without interrupting service to the outgoing (O/G) lines.

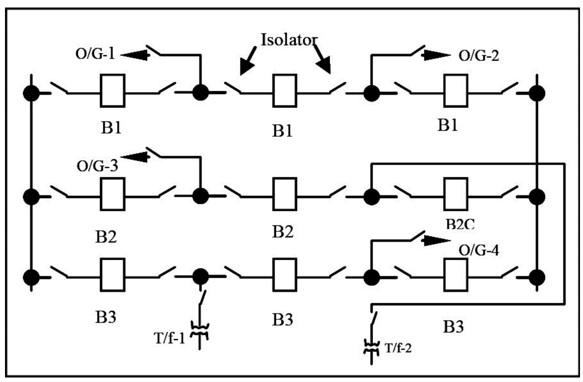

FIG. 1 BREAKER AND HALF BUSBARS SCHEME

If a center breaker fails, this causes the loss of both the circuits, while the loss of an outside breaker disrupts the corresponding circuit only. This scheme has the highest flexibility and reliability during the maintenance. The breaker and half scheme is a popular choice while upgrading a ring bus to provide more terminals. The advantages of this scheme are flexible operation and high reliability, double feed to each circuit, isolation of either bus or any breaker for maintenance without service disruption. The disadvantages of this scheme are more complicated relaying as the central breaker has to act on faults for either of the 2 circuits associated with it. The main purpose of consideration of breaker and half bus-bar scheme is to observe its impact on the placement of PMUs. The placement method proposed in this paper considers the breaker and half bus-bar scheme for one test system i.e., WSCC-9 bus system.

3.0 PROPOSED METHOD

The OPP problem is binary in nature, whose objective is minimization of installation cost. The constraint is that minimum one PMU at each end of the line making system fault observable. The PMU placement problem formulated using ILP is as follows:

$$\min \sum_{i=1}^{N} C_i x_i \tag{1}$$

Subject to

$$f_j(X) \geq 1 \tag{2}$$

where x_i is the vector whose entries are one if PMU is placed at ith bus and zero otherwise. C_i is the cost PMU installation at ith bus which is assumed 1 pu. f_i is the observability constraint at jth line and the ILP can be illustrated with help of a 6 bus example shown in Figure 2.

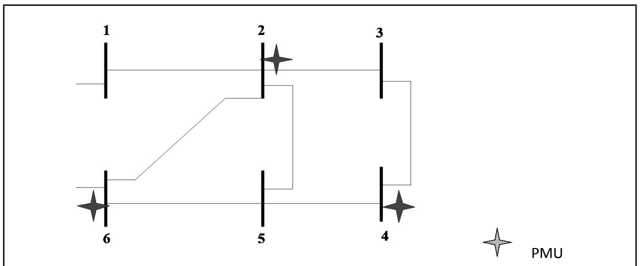

FIG. 2 6 BUS EXAMPLE [3]

The constraints are as given in eq. (3). The first constraint $x_1+x_2\geq1$ makes the line 1–2 observable by placing minimum one PMU. The solution of the above ILP problem for the line observability, using Matlab 7.0, is {2, 4, and 6}. For bus observability [6], the PMUs will be placed at {2, 5} which will make lines 1–6, 3–4 unobservable under fault occurrence, as the line parameters are going to change

$$\begin{aligned} f_1 &: x_1 + x_2 \geq 1 \\ f_2 &: x_2 + x_3 \geq 1 \\ f_3 &: x_3 + x_4 \geq 1 \\ f_4 &: x_4 + x_5 \geq 1 \\ f_5 &: x_5 + x_2 \geq 1 \\ f_6 &: x_5 + x_6 \geq 1 \\ f_7 &: x_6 + x_2 \geq 1 \end{aligned} \tag{3}$$

The observability of power system refers to unique determination of all its states. So, separate PMU placement is needed for the fault diagnosis. It is to be observed that the proposed OPP makes system completely line observable even under fault occurrences. Once the placement is done, a real power based (N-1) contingency analysis is carried out for finding the critical lines. The critical lines are the lines with high Performance Index (PI) obtained from the contingency ranking. The real power based performance index is as given below

$$PI = \sum_{m=1}^{N_l} \frac{W_m}{2n} \left(\frac{P_{lm}}{P_{lm}^{max}} \right)^{2n}$$

where,P_{lm} is the real power flow and P_{lm}^{max} is the rated capacity of the line-*m*, *n* is the exponent and W_m is the real non-negative coefficient which may be used to reflect the importance of the lines. N_l is the total number of lines in the transmission network. The lines with high PI are considered to be more critical and various faults are posed on the lines and the data is collected from the PMUs and are given to the SVM which is done in two phases.

In phase-I, three SVM-Classifiers (SVM-C), are used for fault detection, faulted line identification and fault classification. In phase-II, four support vector regressors are used, in which, two cycles of the time-stamped voltage and current phasors during fault and fault type information obtained from the phase-I are given as input feature vector for finding out fault distance from the PMU located bus. The phasor reporting rate considered for 60 Hz is 60 phasors per sec. The input vector for SVM consists of phasor voltages of the buses where PMUs are placed and phasor currents of flowing through the lines emanating from the PMU bus. The block diagram for the phase-I is shown in Figure 3.

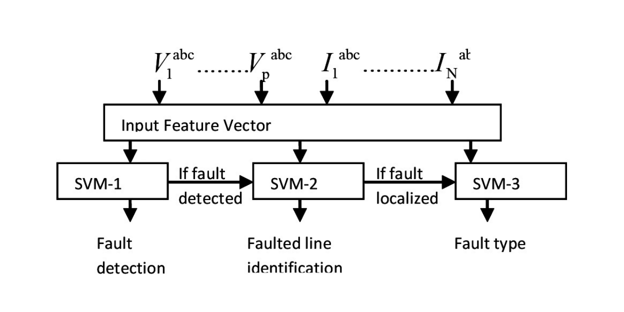

FIG. 3 BLOCK DIAGRAM FOR THE SVM CLASSIFICATION

The proposed OPP ensures complete observability of all the transmission lines of the system. The SVM-1 takes both pre-fault and during fault data of one cycle each, for detecting whether fault has taken place or not. For achieving good decision, pre-fault data is also taken into consideration. The output can be either 0, no fault condition or 1, fault condition. The SVM-2 and SVM-3 take one cycle of data at the fault instance for faulted line identification and fault classification. Dimension of the input pattern is given by total number of transmission lines in the system and voltages of the PMU buses.

Transmission lines are subjected to wide-variety of faults, which include Single Line-to-Ground (SLG), Double Line-to-Ground (DLG), Double line (LL) and Three-phase (LLL) faults. The training and test patterns are generated for above mentioned four types of faults with varying fault impedance values and at different locations of the transmission line. For locating the fault distance, four SVM regressors are used for finding fault distance from the PMU bus. The phase-II input features include the fault type information along with voltage and current phasors as shown in Figure 4.

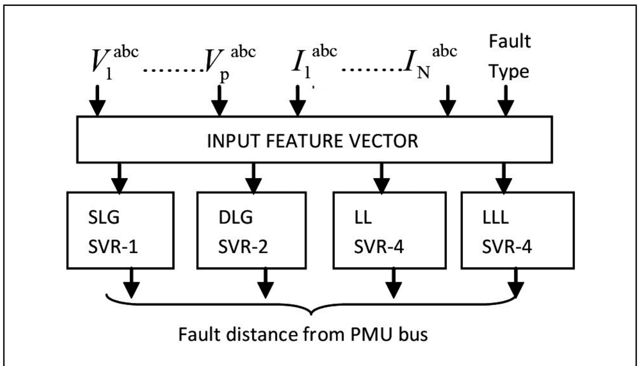

FIG. 4 BLOCK DIAGRAM FOR THE SVM REGRESSION

4.0 SUPPORT VECTOR MACHINE AND RADIAL BASIS FUNCTION NEURAL NETWORKS

4.1 Support Vector Machine

Support vector machine [17,19] is an intelligent learning method for pattern recognition and and promising method for learning the separating functions used in the classification tasks, or for performing function estimation in the regression analysis. The SVM uses supervised learning to classify data into two or more classes. SVMs were originated from the statistical learning theory proposed by Vapnik [1] for 'distribution-free learning from data'. The use of SVM is a remedy among other alternatives such as fuzzy logic, Neural Networks (NN) or Genetic Algorithms (GA), which generally suffers from the presence of multiple local minima, structure selection problem e.g. number of hidden layer nodes in NNs, population size in GAs and over-fitting.

4.1.1 SVM-Classification

A classification task usually involves training and testing data, which consists of some data instances. Each instance in the training set contains one "target value" (class labels) and several "attributes" (features). The goal of SVM is to produce a model which predicts target value of the data instances in the testing phase when only the attributes are given. The Support Vector (SV) methods construct the optimal separating hyperplane for pattern recognition. If the data set is linearly separable, the required number of SVs can be small. Consequently, the hyperplane is determined by a small subset of training data set. When there is no separating hyperplane, the goal of SVM is to maximize the margin.

Consider a training set of instance-label pairs (x_i, y_i), i=1, ..., l where $x_i \in R^n$ and $y_i \in \{-1,1\}^l$ and l is the number of instances. The optimization criterion to obtain the (optimum) separating hyperplane [17] is taken as,

$$\min_{w,b,\xi} \frac{1}{2}\left|w^2\right| + C\left(\sum_{i=1}^{l} \xi_i\right) \tag{4}$$

subject to

$$y_i\left(w.x_i + r\right) \geq 1 - \xi_i, \xi_i \geq 0 \forall i \tag{5}$$

Its dual form can be written as

$$\min_{\alpha} \frac{1}{2}\alpha^T Q\alpha - e^T \tag{6}$$

subject to

$$y^T \alpha = 0,\ 0 \leq \alpha \leq C,\ i=1,...\ l \quad (7)$$

where e is the vector of all ones, C > 0 is the upper bound, $Q_{ij} \equiv y_i y_j$ K (x_i, x_j) is a $l \times l$ positive semi-definite matrix, and $K\left(x_i, x_j\right) = \phi^T\left(x_i\right)\phi\left(x_j\right)$ is the kernel. Here, the training vector x_i is mapped into high dimensional space with bias by the function Φ. The decision function [15] is given by,

$$\operatorname{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i K\left(x_i, x_j\right) + b\right) \tag{8}$$

SVMs are designed for binary classifiers. Currently, there are two types of approaches for multi-class problems. One is constructing and combining several binary classifiers, while the other is by considering all the data in a single optimization formulation. In the former approach, methods like 'one-against-one' and 'one-against-all' have been proposed, where multi-class problem is solved by combining several binary classifiers. In this work, 'one-against-one' method [18] is used for multi-class classification, because of its less learning time over 'one-against-all'. Often, in order to find the suitable boundary between two classes, the SVM has to map the data from the input space to high dimensional space. The function that performs this mapping is called a 'kernel function'. The choice of kernel function and its parameter settings are important elements in designing SVM. There are different types of kernels, to train the SVM, where Radial basis function (RBF) kernel is given by

$$K(x_i, x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right)\gamma > 0 \tag{9}$$

The RBF kernel is used in this work. For training of the SVM for any classification and regression problem, an approximate representation of examples as well as model parameters C,γ and $K(x_i,x_j)$ selection play a key role in achieving the high performance of the machine learning. The penalty parameter Cis a regularization parameter that controls the tradeoff between maximizing the margin and minimizing the training error. The kernel functionK (x_i, x_j) and $\gamma\left(\gamma = \frac{1}{\sigma^2}\right)$ (σ is the width of the kernel) implicitly defines the nonlinear mapping from input space to high dimensional feature space. It is found that larger C corresponds to less number of support vectors as well as higher testing accuracy although over-fitting cannot be avoided. Training of the SVM requires selection of the parameter C and kernel parameters to obtain good performance. Interactive grid search is used to estimate the parameters.

4.1.2 SVM-regression

SVMs are originally developed to solve classification problem However recently these have been extended to the regression problems [17]. The support vector regressor model depends only on a subset of training data, as the cost function for building the model ignores any training data close to model prediction (within a threshold ε). Given a set of training samples, one wants to learn a regression function as given below,

$$f(x) = w^T x + b,\ w, x \in R^N \text{ and } b \in R \tag{10}$$

The regression can be solved through an optimization problem presented in [15]. The regressor used here, is υ-SVR, with (C, ν) as parameters υ-SVR solves,

$$\min_{w,b,\xi,\xi^*,\varepsilon} \frac{1}{2} w^T w + C\left(\upsilon\varepsilon + \frac{1}{l}\sum_{i=1}^{l}\left(\xi_i - \xi_i^*\right)\right) \tag{11}$$

subject to

$$\left(w^T \phi\left(x_i\right) + b\right) - z_i \le \varepsilon + \xi_i,$$

$$\xi_i, \xi_i^* \ge 0, i = 1, \ldots, l, \varepsilon \ge 0 \tag{12}$$

It is proved in [18], ν is an upper bound on the fraction of training errors and a lower bound of the fraction of support vectors.

4.2 Radial Basis Neural Networks

Radial basis neural network is a feed forward neural network, which has good fitting ability and fast training speed. The RBFNN used in this paper for comparison with SVM method, has an input layer, a hidden layer consisting of Gaussian node function, a set of weights w connecting hidden layer and the output layer. Let x be the input vector $x = (x_1, x_2, \ldots, x_D)^T$ and output vector $o = (o_1, o_2, \ldots o_N)$ (where D is the number of nputs and N is the number of output nodes. For an input x (t) and p training patterns, RBFNN approximation at the jth output node is given by

$$o_j(t) = \sum_{i=1}^{m_{tot}} w_{ij}\phi_i(t) + b$$

$$= \sum_{i=1}^{m_{tot}} w_{ij} e^{\frac{-\left\|x(t) - c_i\right\|}{2\sigma_i}} + b \tag{13}$$

where c_i is the ith hidden node, σ_i is the width of the ith center and m_{tot} is the total number of hidden nodes. Training of RBFNN involves selecting centers, estimating weights and bias b that connect hidden layer and output layer. The network begins with no hidden units and as observations are received, new hidden units are added by taking some of the input data.

5.0 SYSTEM STUDIES

The proposed method is tested on WSCC-9 bus system and New England (NE)-39 bus system. Matlab/Simulink 7.0 is used for all the fault simulations and LIBSVM [18] toolbox is utilized for fault classification and location. Various faults are created by varying fault impedances and the synchrophasor voltage and current measurements are assumed to be available at the PMUs. For training patterns, faults are created at 5, 15, 25, 35, 45, 55, 65, 75, 85 and 95 percentage of the overall length of the transmission lines. Therefore, the training patterns are generated for four types of faults on all the lines over 10 different locations having six impedance values of 2, 5, 10, 20, 50 and 100 ohms. Test patterns are generated for the same four faults at distances 20, 40, 60 and 80 percentage of overall length of the transmission line and the impedance values considered are 3, 7, 15, 30, 40 and 60 ohms.

The input patterns for both training and testing of the SVM and RBFNNs are normalized between (–1, 1) and then utilized for the classification and regression. The PMUs placement for both the test systems is as given in the Table 1. Thus, the proposed scheme applied on the test system results in OPP at buses 4, 7, 9 and 10 for configuration-1 and buses 4, 7 and 9 for the configuration-2 of the WSCC-9 bus and 18 PMUs for the NE-39 bus system making both the systems complete transmission line fault observable as shown in Figures 5–7 respectively.

TABLE 1

OPP FOR WSCC-9 BUS AND NE-39 BUS SYSTEMS

System		OPP
WSCC-9 bus	Configuration-1	4, 7, 9, 10
	Configuration-2	4, 7, 9
NE-39 bus		2,4,6,8,10,12,14,16,17,18,19,20,22,23,25,26,29,39

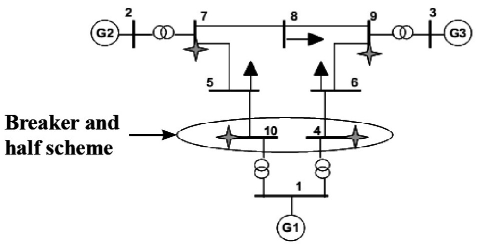

FIG. 5 WSCC-9 BUS SYSTEM CONFIGURATION-1

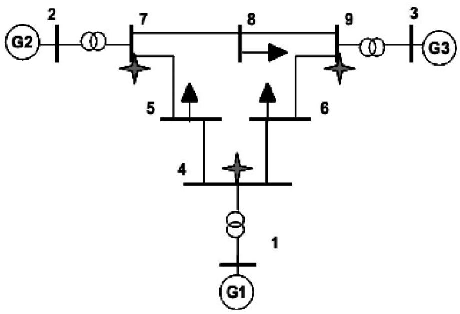

FIG. 6 WSCC-9 BUS SYSTEM CONFIGURATION-2

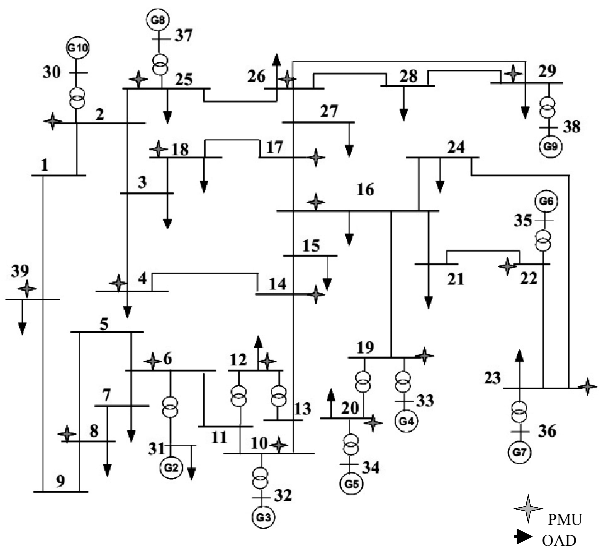

FIG. 7 NE-39 BUS SYSTEM WITH OPP

5.1 WSCC-9 bus System

Breaker and half busbars scheme is implemented for the WSCC-9 bus system, in which two configurations are considered and shown in Figures 5 and 6. It is assumed that at the bus 4, breaker and half bus-bars scheme is installed.

5.1.1 SVM based fault diagnosis

Training patters are generated for four types of faults i.e., SLG, DLG, LL and LLL faults, on all the 6 transmission lines over 10 different locations with 6 varying impedance values. The total patterns are 360 (=6×10×6) for each type of fault. Test patterns are generated for four faults on all lines over 4 different locations with 6 varying impedance values and a total of 6×4×6=144 for each fault type. Tables 2 and 3 give the training and testing accuracies of the SVM classifiers. For configuration-1, the SVM-1 detects fault with 100% testing accuracy and SVM-2 gives 96.8% testing accuracy for line on which fault has taken place whereas SVM-3 gives 94.4 % testing accuracy for classifying the fault. For configuration-2, the SVMs 1, 2 and 3 gives 100% accuracy for detecting a fault, fault line identification and fault classification. The fault location using four support vector regressors (SVRs) is carried out for the same training and test patterns, which are used in SVM-classification. The SVR-1, SVR-2, SVR-3 and SVR-4 give the locations of SLG, DLG, LL and LLL faults,

TABLE 2

SVM PHASE-I RESULTS FOR WSCC-9 BUS SYSTEM (CONFIGURATION-1)

Classifier	C	γ	Training accuracy	Testing accuracy
SVM-1	0.125	0.0078125	100 %	100 %
SVM-2	2048	0.03125	100 %	96.805 %
SVM-3	0.5	0.5	100 %	94.94 %

TABLE 3

SVM PHASE-I RESULTS FOR WSCC-9 BUS SYSTEM (CONFIGURATION-2)

Classifier	C	γ	Training accuracy	Testing accuracy
SVM-1	0.5	0.0078125	100 %	100 %
SVM-2	2048	0.03125	100 %	100 %
SVM-3	2.0	0.5	100 %	100 %

respectively. Table 4 presents the fault location for WSCC-9 bus system without breaker and half scheme consideration. The fault location results are shown for the line 1–4, which came out to be critical line by real power performance index based contingency analysis. The percentage error in fault location is given by

$$\%\ \text{Estimation error} = \frac{\text{Estimated location} - \text{Actual location}}{\text{Total line length}} \times 100$$

The SVM regressors are provided with one cycle of fault data i.e., for 1 phasor per cycle of 50 Hz system, the phasor reporting rate is 50 phasors per sec. The fault distance estimation for various types of faults with two fault resistance values is given in Table 4. The SVM-1 detects fault and SVM-2 identifies the line and SVM-3 classifies the fault. The SVR-1 gives the SLG fault location with C=100, $\nu = 0.1$ and $\gamma = 0.5$, SVR-2 gives the DLG fault location with C = 1000, $\nu = 0.5$ and $\gamma = 0.5$, SVR-3 gives the LL fault location with C=100, $\nu = 0.05$ and $\gamma = 0.5$, SVR-4 gives the fault location with C = 1000, $\nu = 0.1$ and $\gamma = 0.01$ which are shown in Table 4.

TABLE 4

FAULT LOCATION COMPARISON RESULTS FOR WSCC-9 BUS SYSTEM

Fault locators		**Maximum % error**	**Minimum % error**
SVR	SVR-1	0.093	$9.5e^{-4}$
	SVR-2	0.137	$2.65e^{-4}$
	SVR-3	0.8	$5.64e^{-4}$
	SVR-4	0.7255	0.017
RBFNN	RBFNN-1	0.62	0.009
	RBFNN-2	1.245	$3.75e^{-4}$
	RBFNN-3	1.395	$6.8e^{-4}$
	RBFNN-4	2.45	$0.86e^{-4}$

5.1.2 RBFNN based fault diagnosis

The RBFNNs are trained with the same training and test patterns that are generated for SVM. Selection of proper spread values which determine the width of the radial basis function in designing RBFNN. For the configuration-1, the optimized values of spread, hidden neurons and testing accuracy for the RBFNN are given below:

- **RBFNN-1**: 375 hidden neurons and 0.5 spread provides 99.89% testing accuracy.
- **RBFNN-2**: 625 hidden neurons and spread 1.1 provides 91.32 % testing accuracy.
- **RBFNN-3**: 575 hidden neurons and spread 0.707 provides 93.25 % testing accuracy.

For the configuration-2, the optimized values of spread, hidden neurons and testing accuracy for the RBFNN-1 to RBFNN-3 are, 175 hidden neurons and 1.1 spread provides 99.19 % testing accuracy, 625 hidden neurons and spread 1.05 provides 98.82 % testing accuracy, 775 hidden neurons and spread 0.707 provides 99.30 % testing accuracy, respectively.

For fault location, four RBFNNs are given the same input patterns that are used for the fault location using SVM. The optimized values for locating fault using RBFNN after number of observations are spread=0.5, hidden neurons=175 for SLG fault, spread=0.707, hidden neurons=175 for DLG fault, spread=1.05, hidden neurons=200 for LL fault and spread=1.0, hidden neurons=200 for LLL fault obtained from RBFNNs 1, 2, 3 and 4, respectively. Table 5 gives the comparison between SVR and RBFNN fault location methods, from which it is clear that SVM fault locator gives better estimate of the fault distance than RBFNN. Figure 8 shows the fault location error estimate in percentage for all the four fault types of WSCC-9 bus system, configurations-1 and 2.

TABLE 5

SVM-C RESULTS FOR NE-39 BUS SYSTEM

Classifier	**C**	**γ**	**Training accuracy**	**Testing accuracy**
SVM-1	0.125	0.0078125	100 %	100 %
SVM-2	8192	0.03125	100 %	99.814 %
SVM-3	32	0.0001225	97.22 %	100 %

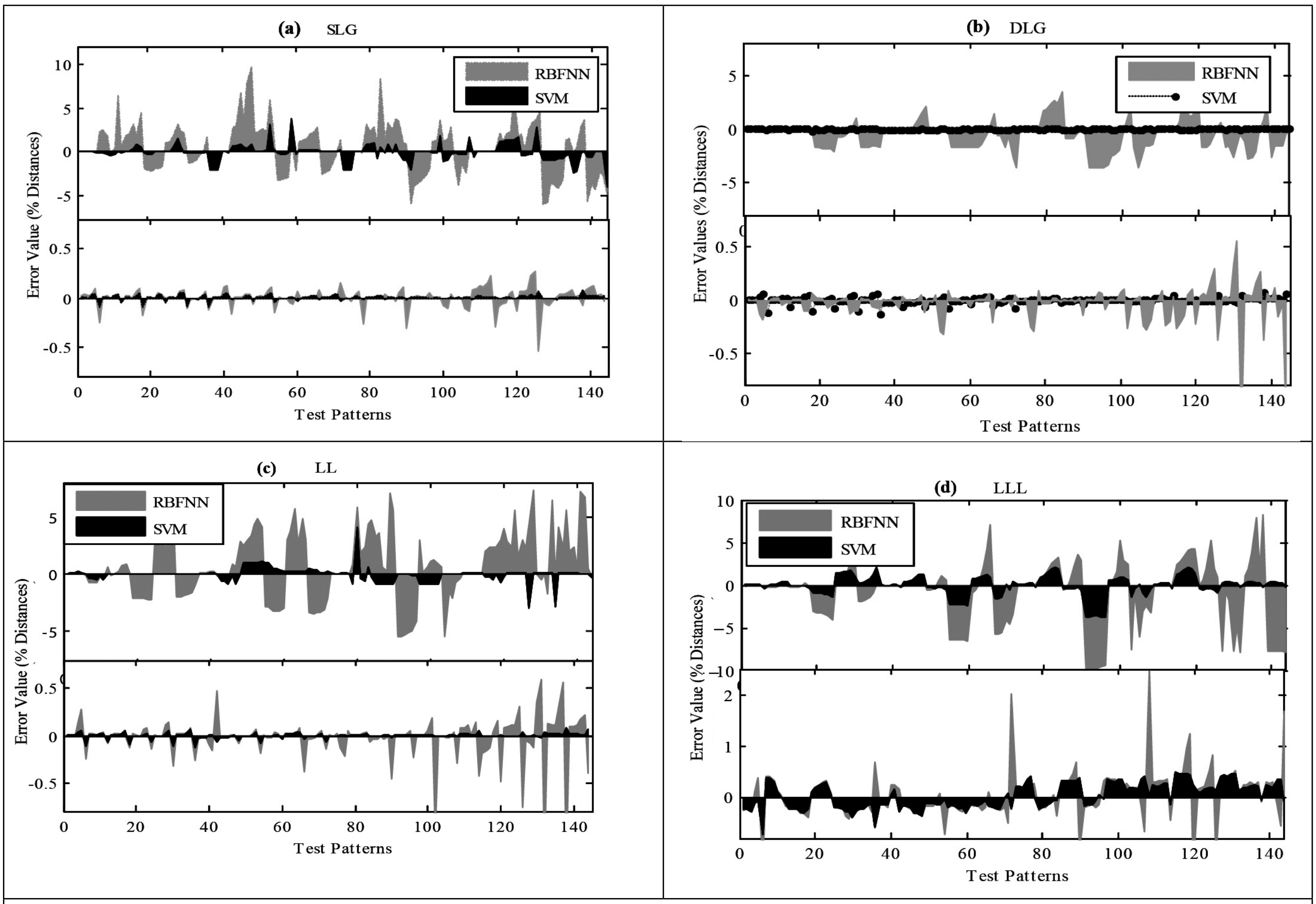

FIG. 8 SLG, DLG, LL AND LLL FAULTS WITH UPPER FIGURE FOR CONFIGURATION-1 AND LOWER FIGURE FOR CONFIGURATION-2 OF WSCC-9 BUS SYSTEM AS SHOWN IN (A), (B), (C) AND (D) RESPECTIVELY

5.2 NE-39 bus System

5.2.1 SVM based fault diagnosis

Training patters are generated for four types of faults on 10 transmission lines selected by conducting contingency ranking using real power security index over 10 different locations with 6 varying impedance values, a total of 10×10×6=600 for each type of fault. Test patterns are generated for four faults on selected 10 critical lines over 4 different locations with 6 varying impedance values and a total of 10×4×6=240 for each fault type. Table 6 presents the training and testing accuracies of the SVM classifiers. The SVM-1 detects the fault with 100 % testing accuracy, SVM-2 gives 99.81 % testing accuracy for line on which fault has taken place and SVM-3 gives 100 % testing accuracy for classifying the fault. Once the fault has been classified, the next step is to locate the fault. Figure 9 shows the fault location error in percentage values for the lines which came to be critical by real power performance based contingency analysis for all the four fault types. The SVR-1 gives the SLG

TABLE 6

FAULT LOCATION COMPARISON RESULTS FOR NE-39 BUS SYSTEM

Fault locators		**Maximum % error**	**Minimum % error**
SVR	SVR-1	3.85	0.0355
	SVR-2	4.002	0.011
	SVR-3	0.145	$6e^{-4}$
	SVR-4	3.8	0.02
RBFNN	RBFNN-1	8.425	0.0017
	RBFNN-2	8.34	0.0275
	RBFNN-3	6.39	0.0525
	RBFNN-4	8.04	0.0105

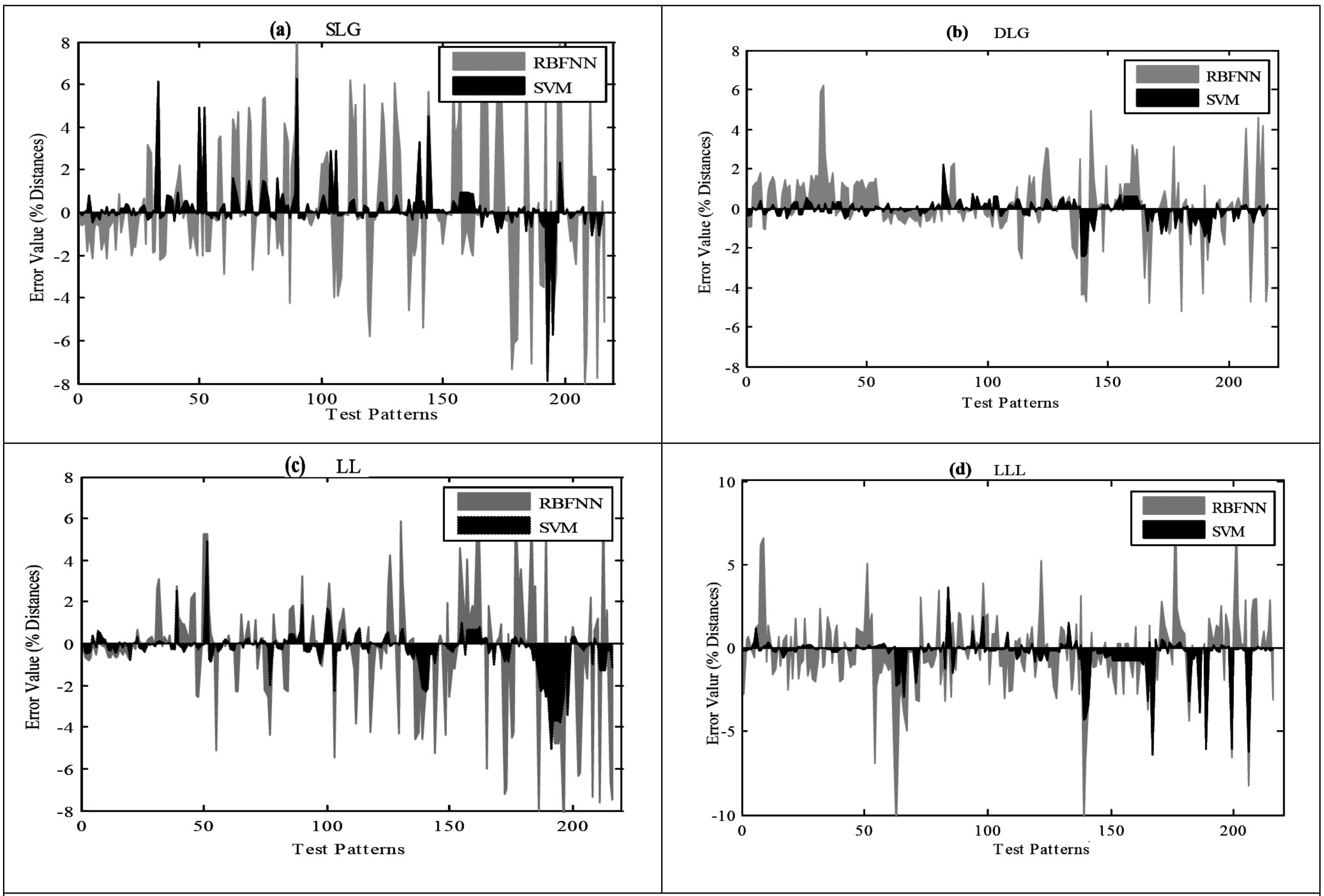

FIG. 9 SLG, DLG, LL AND LLL FAULTS FOR NE-39 BUS SYSTEM AS SHOWN IN (A), (B), (C) AND (D) RESPECTIVELY

fault location with C = 10, ν and $\gamma = 0.5$, SVR-2 gives the DLG fault location with C = 100, $\nu = 0.1$ and $\gamma = 0.1$, SVR-3 gives the LL fault location with C = 100, $\nu = 0.1$ and $\gamma = 0.5$, SVR-4 gives the fault location with C = 1000, $\nu = 0.01$ and $\gamma = 0.5$.

5.2.2 RBFNN based fault diagnosis

The RBFNNs are trained with the same training and test patterns that are generated for SVM. Selection of proper spread values which determines the width of the radial basis function is important in designing RBFNN. The optimized values of spread, hidden neurons and testing accuracy for the RBFNN-1 to RBFNN-3 are, 200 hidden neurons and 0.95 spread obtained 99.23 % testing accuracy, 925 hidden neurons and spread 0.707 obtained 94.31 % testing accuracy, 800 hidden neurons and spread 0.707obtained 98.26 % testing accuracy, respectively.

6.0 CONCLUSIONS

In this paper, a topological observability using binary integer programming based method for the optimal placement of the Phasor Measurement Units (PMUs) to ensure transmission line fault observability and a Support Vector Machine (SVM) based fault diagnosis utilizing the synchrophasor measurements have been proposed. The proposed placement of PMU technique has been examined in the presence of breaker and half bus-bars scheme on WSCC-9 bus test system. It is observed that breaker and half scheme application increases the PMUs number by one. The phasor data generated by the PMUs, which are placed optimally in the system, can be effectively used for the transmission line fault diagnosis. It is observed that from the proposed fault diagnosis method, SVM based fault classification and location give high accurate results than compared to RBFNNs.

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