Online Voltage Stability Monitoring and Prediction by Using Support Vector Machine Considering Overcurrent Protection for Transmission Lines

A. H. Poursaeed* and F. Namdari (C.A.)

Abstract: In this paper, a novel method is proposed to monitor the power system voltage stability using Support Vector Machine (SVM) by implementing real-time data received from the Wide Area Measurement System (WAMS). In this study, the effects of the protection schemes on the voltage magnitude of the buses are considered while they have not been investigated in previous researches. Considering overcurrent protection for transmission lines not only resolves some drawbacks of the previous studies but also brings the case study system closer to the realities of actual systems. Online monitoring of system stability is performed by prediction of the Voltage Stability Index (VSI) and carried out by using Support Vector Regression (SVR). Due to the direct effect of appropriate SVR parameters on the prediction quality, the optimum value is chosen for learning machine hyperparameters using Differential Evolution (DE) algorithm. The obtained simulation results demonstrate high accuracy, effectiveness, and optimal performance of the proposed technique in comparison with Back-Propagation Neural Network (BPNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) approaches. The presented method is carried out on the 39 bus New England system.

Keywords: Voltage Stability, Support Vector Machine, Overcurrent Protection, Wide Area Measurement System, Differential Evolution.

1 Introduction

Stability always has been a fundamental issue in the field of power systems generation and transmission, which has become more complicated than ever before with the physical growth and parallel connection of the generators [1]. According to the recorded reports of the main reasons for worldwide blackouts in recent years, voltage instability is among the most serious threats to the safe operation of the power systems, [2]. Today, WAMS technology, with the aid of Phasor Measurement Units (PMUs), has enabled the monitoring of the dynamic model of the power system in real-time to improve the observability of power system stability status [3].

Nowadays, with the increasing installation of PMUs in power systems, some Machine Learning techniques such as Artificial Neural Networks (ANN), Fuzzy Logic (FL), Decision Trees (DTs), ANFIS, and SVMs are used to assess voltage stability of the system. ANN has been used to estimate voltage stability status under normal and abnormal conditions [4] as well as to find the minimum input variables to fast estimation of the voltage stability margin with high accuracy [5, 6]. Reference [7] proposes a prediction of voltage stability margin using RBF neural network and performs feature extraction for the voltage profile of the buses using wavelet analysis and Principal Component Analysis (PCA). In [8], a functional estimation of steady-state voltage stability limits is proposed by calculating the critical values of the minimum singular values and the tangent vector norm using ANN. In [9], a voltage stability assessment criterion based on implementing of DT algorithm is proposed. According to a predetermined pattern and load-generation variation scenarios, continuous load flow calculations are performed. Then, the system is labeled as safe or unsafe...
on each operating point of the system. Authors in [10] train a DT by reducing the dimension of the received data from WAMS using PCA. Then, the important branches through the feature selection technique are identified. Finally, the system security degree is determined. The application of FL to estimate the voltage magnitude of the load buses for every possible contingency is discussed in [11]. Reference [12] also measures the margin of the current operating point to the collapse point using ANFIS and an automatic voltage stability assessment tool. In [13], an estimation of the system loadability margin considering the uncertainty of the load with high accuracy using an ANFIS based on subtractive clustering has discussed. References [14-16], first calculate a voltage stability index, then predicts the values of the voltage stability indices using SVR. Also, SVR hyperparameters are optimized by GA, DragonFly Optimization Algorithm (DOA), and Particle Swarm Optimization (PSO), respectively. GA has many disadvantages, such as adjustment for choosing appropriate operators and premature convergency. PSO also has many parameters to choose that affect the performance of the algorithm. However, DOA is easier to use than PSO and GA but has trouble in trapping to the local minimum. In [17], by performing online contingency analysis, three different indices are considered for each induction machine of the system. When a fault occurs, the time series of the induction machines slip is calculated using real-time data received from PMUs. Afterward, through the Least Square-Support Vector Machine (LS-SVM), time series prediction is performed and the voltage instability index is predicted by slip trajectory monitoring. Although LS-SVM has a lower computational burden than SVM and solves a linear programming problem instead of a quadratic programming problem, but it has loss of sparseness. Reference [18] also addresses the use of SVM in voltage stability prediction and monitoring for distribution systems and the advantage of PSO based SVM over GA-SVM. The Prediction of the load margin using real-time data from PMUs using SVM has been studied in [19]. Due to its higher speed of the mentioned method compared to others, control actions can be taken early to prevent voltage collapse. Also with the injection of reactive power into the weakest buses by FACTS devices, voltage stability status could be improved. The main drawback of this paper is that it compares the different methods without tuning their hyperparameters, while the proper selection of these quantities has a direct impact on the prediction process. The mentioned papers have not considered the effect of the protective relays systems on voltage monitoring of the actual systems. The operation of the protective relays changes the configuration of the system under normal conditions. Since the protection system operation causes a step transition in the system graph (i.e. a line outage due to relay operation causes a step change in the measurements), in this study these binary effects of the protective relays on the nonlinear system have been considered. Also, previous studies are not applicable to the online prediction of voltage stability while the proposed method is tested online and is compatible with Wide Area Monitoring, Protection and Control (WAMPAC) system.

This paper has considered the effect of the protective relay operations on voltage stability while the previous studies do not. Then, a comprehensive scheme is proposed to online monitoring and predicting of voltage stability using a DE based SVR (DE-SVR). In the presented scheme, overcurrent protection is considered for the transmission lines of the system under study. Optimal coordination of Directional Overcurrent Relays (DOCRs) has also been established by implementing the Genetic Algorithm (GA). Then, a time-domain based index is considered to evaluate the voltage stability status of this proposed scheme which is predicted by SVR. To improve the accuracy of the prediction, the hyperparameters of this learning machine are obtained using the DE algorithm. DE has less parameter to adjust, high convergence speed and it is easy to implement. Finally, the results of the proposed method are discussed and compared with BPNN and ANFIS. The proposed method has been implemented on the 39 bus New England system.

The rest of the paper organized as follows. Section 2 describes the index of voltage stability assessment and optimal coordination of DOCRs. Section 3 investigates the structure of SVMs and SVRs. Section 4 presents the proposed method. Section 5 is simulation results and discussion about comparison of the proposed method with BPNN and ANFIS approaches. Finally, the conclusion represents in Section 6.

2 Problem Formulation

2.1 Voltage Stability Assessment

Voltage stability refers to the ability of the system to maintain the voltage magnitude of all of the buses at an acceptable steady-state value in whether normal or abnormal operating conditions. Numerous studies have been conducted to evaluate the system voltage stability by providing various indices [20]. In [21], a voltage stability index using real-time data received from WAMS has been introduced. This index called Voltage Stability Index (VSI) and measures the voltage stability margin. Also, one of the voltage stability evaluation indices is defined for the transmission lines of the power system. The basis for the calculation of VSI is based on the simple two-stroke power system as shown in Fig. 1.

The VSI is defined as (1):

\[
VSI = \min \left( \frac{P_{margin}}{P_{max}}, \frac{Q_{margin}}{Q_{max}}, \frac{S_{margin}}{S_{max}} \right)
\]
where $P_{\text{margin}}$, $Q_{\text{margin}}$, and $S_{\text{margin}}$ are the margins of active, reactive, and apparent power at the end of the line (receiving end), respectively. These parameters are defined as (2)-(4).

\[
P_{\text{margin}} = P_{\text{max}} - P_r \\
Q_{\text{margin}} = Q_{\text{max}} - Q_r \\
S_{\text{margin}} = S_{\text{max}} - S_r
\]

(2)

(3)

(4)

where $P_{\text{max}}$, $Q_{\text{max}}$, and $S_{\text{max}}$ are the maximum active, reactive, and apparent power at the end of the line, respectively, as well as $P_r$, $Q_r$, and $S_r$ are the active, reactive, and apparent power received at the receiving end. These parameters are also expressed as (5)-(10).

\[
P_{\text{max}} = \sqrt[4]{\frac{V_r^4}{4X} - \frac{V_r^2}{X}}
\]

(5)

\[
Q_{\text{max}} = \frac{V_r^2}{4X} - \frac{P_r^2 X}{V_r^2}
\]

(6)

\[
S_{\text{max}} = \left(1 - \sin\left(\arctan\frac{Q_r}{P_r}\right)\right)V_r^2
\]

(7)

\[
P_r = \left(V_r \cos(\delta_r - \delta_r) - V_r\right)\frac{R}{R^2 + X^2} + V_r \sin(\delta_r - \delta_r)\frac{X}{R^2 + X^2}
\]

(8)

\[
Q_r = \left(V_r \cos(\delta_r - \delta_r) - V_r\right)\frac{X}{R^2 + X^2} - V_r \sin(\delta_r - \delta_r)\frac{R}{R^2 + X^2}
\]

(9)

\[
S_r = P_r + jQ_r
\]

(10)

VSI is considered stable if it is greater than zero (positive value) and when the value equal to zero, the system will go to the voltage collapse point.

2.2 Overcurrent Protection

One of the major effects of the fault in the power system is the occurrence of a sudden large current that flows through the system. Therefore, the amplitude of the current can be used as one of the signs of the incident of a fault in the system. So overcurrent protection is one of the most efficient protection schemes that is widely used in power systems as primary and backup protection.

2.2.1 Optimal Coordination of the Directional Overcurrent Relays

Optimal coordination of DOCRs for their fast and efficient performance is a very important issue. Coordination of the protection relays means choosing the right settings for the relays so that their protection function meets the requirements of a protection system under different conditions. These features include sensitivity, selectivity, reliability, and speed. Choosing valid settings for the relays plays a very important role in reducing and isolation of the effect of the faults on the system.

Many studies have been conducted on the problem of optimal coordination using mathematical methods, artificial intelligence-based methods, and a combination of these two approaches [22]. In recent years, optimal coordination of DOCRs with Quadratic Constrained Quadratic Programming (QCQP) [23], Mixed Integer Linear Programming (MILP) [24], Biogeography-Based Optimization-Linear Programming (BBO-LP) [25], Gravitational Search Algorithm-Sequential Quadratic Programming (GSA-SQP) [26] and the hybrid heuristic methods such as Gravitational Search Algorithm-Particle Swarm Optimization (PSO-GSA) [27] have also been solved. Reference [28] proposed a new objective function to optimally solve the DOCRs coordination problem that addresses the problems of miscoordination between primary and backup relays and the larger operating time of backup relays in previous studies has resolved.

The general form of Inverse Definite Minimum Time (IDMT) overcurrent relay operating time is defined by IEC 60255 and IEEE C37.112 [29], and is given in (11):

\[
t_i = \frac{\alpha}{\left(\frac{I_{\text{TMS}}}{I_{\text{pu}}}\right)^\beta + \gamma} - 1
\]

(11)

where $t_i$ is operating time the relay $i$, and $T_{\text{MIS}}$ and $I_{\text{pu}}$ are time multiplier setting and pickup current of the relay $i$, respectively. Also, $I_{\text{pu}}$ is the fault current passing through the main relay, $\alpha$, $\beta$, and $\gamma$ are the constant values. Table 1 provides the constant values of the parameters for curves defined by IEEE C37.112 and IEC 60255.

The most commonly used objective function of the optimal coordination problem of DOCRs (OF1) for a sample power system as shown in Fig. 2, expressed

\[
\text{Table 1: IEEE and IEC constants for standard DOCRs.}
\]

<table>
<thead>
<tr>
<th>IDMT Curve</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moderately (standard, inverse)</td>
<td>0.0515</td>
<td>0.14</td>
<td>0.02</td>
</tr>
<tr>
<td>Very inverse</td>
<td>19.61</td>
<td>13.5</td>
<td>2</td>
</tr>
<tr>
<td>Extremely inverse</td>
<td>28.2</td>
<td>80</td>
<td>2</td>
</tr>
</tbody>
</table>
in (12). This equation is standard inverse IDMT of the IEC standard for DOCRs. The objective is to minimize the operating times of all main relays.

\[
OF1 = \sum_{i=1}^{m} \left( \frac{0.14 \times TMS_i}{I_{pu,i}^{0.02}} - 1 \right)
\]

(12)

where \( m \) is the total number of main relays. The result of optimizing the objective functions of the optimal coordination of DOCRs is to calculate the optimal value for the problem decision variables \( TMS \) and \( I_{pu} \). These decision variables are also bounded and form the constraints of the coordination problem in (13) and (14):

\[
0.1 \leq TMS_i \leq 1.1
\]

(13)

\[
1.25 I_{max,i} \leq I_{pu,i} \leq \frac{2}{3} I_{max,i}
\]

(14)

where, in (13) and (14), \( I_{max,i} \) is the maximum load current and \( I_{max,i} \) is the minimum fault current pass through the relay \( i \).

The proposed objective function in [28], namely POF, is defined to overcome the problems of similar studies in (15):

\[
POF = \alpha_1 \sum_{i=1}^{n} I_{pu,i}^{-1} + \alpha_2 \sum_{i=1}^{n} \left( \Delta I_{pbl} - \Delta I_{pbl}^{2} \right) + \left( \Delta I_{pbl} + \Delta I_{pbl}^{2} \right)
\]

(15)

where \( n \) is the number of primary and backup relay pairs, \( I_{pbl} \) and \( I_{bbl} \) are the operating time of the primary and backup relay for the relay pairs \( k \), respectively. In the end, \( \alpha_1 \) and \( \alpha_2 \) are control parameters to control over both terms in (15). In POF, these two weight factors are considered 1. Also \( \Delta I_{pbl} \), the discrimination time between the relay pairs \( k \), expressed as (16):

\[
\Delta I_{pbl} = I_{bbl} - I_{pbl} - CTI
\]

(16)

\( \Delta I_{pbl} \) is the coordination time interval which is assumed 0.2 seconds in this article. Negative values of \( \Delta I_{pbl} \) indicate that the primary relays have a longer operating time than the backup ones, which may cause miscoordination in the protection system. It should be noted that the computation of \( \Delta I_{pbl} \) for all relay pairs is intended both for fault occurring at the near-end terminal and faults at the far-end terminal.

Due to the nonlinear nature of this objective function, GA is used to minimize POF and then obtain optimal values for decision variables.

2.3 Analysis of the Effect of Considered Overcurrent Protection for Transmission Lines on Voltage Stability

A case study is used to describe the effect of considering overcurrent protection for transmission lines on voltage stability. VSI transient monitoring due to a three-phase short circuit fault occurred at 50% of the transmission line between bus 2 and bus 3 at zero second and its clearance at 0.1 second are examined in the presence and absence of overcurrent protection in Fig. 3. Also, the time interval between 0 to 0.15 seconds is enlarged for better clarity and a description of what happened.

3 Support Vector Machine

Support vector machine is a machine learning technique for the classification of two or more groups of problems. SVM maps nonlinear inputs vectors to a high dimensional feature space. SVM is based on Structural Risk Minimization (SRM) while the neural networks minimize the classification errors [30].

3.1 Support Vector Regression

Support vector regression is an extended model of SVM for the function estimation problem, as shown in Fig. 4 [31]. The SVR estimates the function \( f(x) \) with the training data. These data are defined as \( \{ (x_1, y_1), \ldots, (x_n, y_n) \} \), \( x_i \in \mathbb{R}^n \), where \( x_i \) and \( y_i \) are the input data sets, output data sets, and the total number of the samples, respectively. To estimate voltage stability, \( x_i \) includes voltage magnitude and reactive power for the parameter \( i \), while \( y_i \) is the VSI value for the data \( i \).
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The dual problem of (20) is defined as (22) which is bounded by constraints presented in (23):

\[
\max \left\{ -\frac{1}{2} \sum_{i,j=1}^{n} (\alpha_i^+, \alpha_i^-)(\alpha_j^+, \alpha_j^-) \left( k(x_i, x_j) \right) \right. \\
\left. -\varepsilon \sum_{i=1}^{n} (\alpha_i^+ - \alpha_i^-) + \sum_{i=1}^{n} y_i (\alpha_i^+ - \alpha_i^-) \right\} (22)
\]

\[
\sum_{i=1}^{n} (\alpha_i^+ - \alpha_i^-) = 0 \\
0 \leq \alpha_i^+ \leq C \\
0 \leq \alpha_i^- \leq C
\]

(23)

where \( \alpha_i^- \) and \( \alpha_i^+ \) are lagrangian multipliers, which solve the quadratic problem expressed in (23) and bring the predicted values closer to the actual values. Also, \( k(x_i, x_j) \) is a kernel function that is calculated by the vector product of \( \phi(x_i) \) and \( \phi(x_j) \) in the feature space. The kernel function used in this study is the Gaussian kernel function described in (24):

\[
k(x_i, x_j) = \exp \left( -\frac{||x_i - x_j||^2}{2\sigma^2} \right) (24)
\]

where \( \sigma^2 \) is the bandwidth of Gaussian kernel function.

In this study, \( C, \sigma^2, \) and \( \varepsilon \) obtained by using the DE algorithm.

4 The Proposed Method

First, the optimal coordination of overcurrent relays is performed. The optimal settings for \( TMS \) and \( I_{pu} \) are obtained by using GA according to the procedure described in Fig. 5.

First, primary/backup relay pairs are determined. Then, the initial population is generated, and accordingly, \( TMS \) and \( I_{pu} \) are assigned a value. Given these values, the fitness function is evaluated. Next, the GA selection operator is determined. Finally, GA crossover and mutation operators are applied to the population, respectively. If the stop criteria are satisfied, the optimal values for \( TMS \) and \( I_{pu} \) are obtained. The assumed parameters for GA are shown in Table 2.

In this paper, we assume that the data is received from the PMUs installed in the understudy system to make it observable. The flowchart of the proposed method is shown in Fig. 6. By using these data corresponds to

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
Parameters & Settings \\
\hline
Generations & 1000 \\
Population size & 100 \\
Cross-over rate & 0.95 \\
Mutation rate & 0.01 \\
Selection type & Standard roulette wheel \\
\hline
\end{tabular}
\end{table}
Fig. 5 Optimal coordination of DOCRs using GA flowchart.

Fig. 6 Flowchart of the proposed method.

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The minimization objective function by using the DE method is the MSE function that expressed in (25):

$$\min \left\{ \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left( y_i - y_p \right)^2 \right\}$$

(25)

where \( n \), \( y_i \), and \( y_p \) are the number of samples, the actual values, and the predicted values, respectively. The setting parameters of the DE algorithm and the limits of the SVR hyperparameters are presented in Table 3.

To compare the performance of prediction accuracy three performance evaluation indices MSE, RMSE, and MAE are used which are defined in (26) to (28), respectively. The smaller the value of these indices (near zero) leads the higher the prediction accuracy.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left( y_i - y_p \right)^2$$

(26)

$$\text{RMSE} = \left\{ \frac{1}{n} \sum_{i=1}^{n} \left( y_i - y_p \right)^2 \right\}^{1/2}$$

(27)

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - y_p \right|$$

(28)

Another performance index, called the correlation index or \( R \), is defined, which is defined by (29):

$$R = \frac{\sum_{i=1}^{n} \left( y_i - \bar{y} \right) \left( y_p - \bar{y}_p \right)}{\sqrt{\sum_{i=1}^{n} \left( y_i - \bar{y} \right)^2 \left( y_p - \bar{y}_p \right)^2}}$$

(29)

where \( \bar{y} \) and \( \bar{y}_p \) are rates of the actual and predicted values, respectively. The closer the value of this index to 1 leads to the higher the prediction accuracy.

Table 3 Setting parameters of the DE algorithm.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generations</td>
<td>100</td>
</tr>
<tr>
<td>Population size</td>
<td>40</td>
</tr>
<tr>
<td>Scale factor</td>
<td>0.1-0.9</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.3</td>
</tr>
<tr>
<td>( C )</td>
<td>0.1-1000</td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td>0.1-1000</td>
</tr>
<tr>
<td>( \varepsilon )</td>
<td>0.00001-0.1</td>
</tr>
</tbody>
</table>
5 Results

To demonstrate the effectiveness of the DE-SVR method for online monitoring and prediction of power system voltage stability, the proposed method is applied to the 39 bus New England system. The understudy system, as shown in Fig. 7, comprises 39 buses, 10 generators, 19 loads, and 34 transmission lines. The available DOCRs in transmission lines painted in red to simply distinguish from other equipments.

5.1 Optimal Coordination of DOCRs Using GA

Optimal coordination of DOCRs is done by GA and the optimal settings for $TMS$ and $I_{pu}$ are obtained. The optimal value obtained for POF using GA is 35.2891, while optimal values of the decision variables $TMS$ and $I_{pu}$ are addressed in the Appendix and Table A.1. The convergence diagram of the objective function using GA is shown in Fig. 8.

5.2 The Optimum Values of SVR Hyperparameters Using DE

The results of the DE-SVR method are compared with the ANFIS and BPNN methods with the same data set for all three models. To generating of training 900 consecutive and different load flows ranged from 0.7 times the nominal load to 1.25 times the nominal load performed so that load flow does not diverge. Consecutive load flow is done by using MATPOWER toolbox in the MATLAB environment [32]. These 900 data sets randomly are used as training data and 100 data sets of unseen data through a time-domain study, are used as testing data. Also, in previous papers, SVM testing phases were done offline, so the prediction performance was unknown in real-time. In this study, the testing phase is done online. Therefore, the proposed scheme can be implemented in real-time for online applications in power systems.

Also, the results of optimization for SVR parameters are shown in Table 4 and the DE convergence diagram in Fig. 9.

5.3 Comparison of Results and Discussions

In this section, the prediction accuracy of DE-SVR is compared with BPNN [14], [15] and ANFIS [16] approaches.

a) The BPNN or multilayered perceptron back propagation neural network is the most widely used neural network to solve nonlinear problems including one input layer, one or more hidden layers, and one output layer. This neural network is trained for up to a maximum epoch 100 or when the MSE value is less than 0.001. A training rate of 0.01 and a momentum constant of 0.9 have been assumed for this neural network. In this paper, 2 hidden layers considered while 5 neurons are assumed. It should be noted that the activation function used in this article is the Sigmoid function.

b) ANFIS or adaptive neural-fuzzy inference system that integrates the fuzzy system with an artificial neural network to improve the learning process. The most important factor in ANFIS design is the choice of the Fuzzy Inference System (FIS). In this paper, the subtractive clustering method is used to generate fuzzy rules. Also, the radius of influence in this study is considered to be 0.4.

The comparison between the actual and predicted...
values by the DE-SVR, ANFIS and BPNN models for training data is shown in Fig. 10. The comparison of performance indices for all three methods is shown in Table 5 for the training data to predict VSI.

To generate the testing data, a time-domain study is performed in 0 to 0.1 second time interval with the changes in the static loads in the 39 bus system. The time step for the time-domain simulation is equal to 0.001 seconds. Based on these testing data, the online prediction has been performed by using the proposed methods DE-SVR, ANFIS, and BPNN. A comparison between actual and predicted VSI values in all three methods is shown in Fig. 11.

<table>
<thead>
<tr>
<th>Performance Index</th>
<th>Training Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DE-SVR</td>
</tr>
<tr>
<td>MSE</td>
<td>4.1257e-5</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0064</td>
</tr>
<tr>
<td>MAE</td>
<td>0.0044</td>
</tr>
</tbody>
</table>

**Fig. 10** Comparison between the actual values and predicted ones of VSI in training data: a) DE-SVR, b) ANFIS, and c) BPNN.

**Fig. 11** Comparison between the actual value and predicted ones of VSI in testing data: a) DE-SVR, b) ANFIS, and c) BPNN.
The comparison of performance indices for all three methods is shown in Table 6 for the testing data to predict VSI.

<table>
<thead>
<tr>
<th>Performance Index</th>
<th>DE-SVR</th>
<th>ANFIS</th>
<th>BPNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>5.2746e-5</td>
<td>5.4631e-5</td>
<td>1.2404e-3</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0072</td>
<td>0.0073</td>
<td>0.0352</td>
</tr>
<tr>
<td>MAE</td>
<td>0.0046</td>
<td>0.0042</td>
<td>0.0151</td>
</tr>
</tbody>
</table>

As shown in Tables 5 and 6, the DE-SVR method has higher prediction accuracy due to the smaller performance indices compared to other mentioned approaches either in the training data and the testing data.

The correlation diagram of the actual values vs. the predicted values for the testing data is shown in Fig. 12. Since it can be seen in Fig. 12 and the upper part of each section, the performance of the proposed method is better than the other methods in predicting VSI values in the testing data.

The comparison of the correlation index for all of the three methods is shown in Table 6 for the testing data to predict VSI. As shown in Table 7, the correlation index for DE-SVR is near to 1 that shows the better performance to predict the VSI than the other approaches.

5.4 Comparison between Training and Testing Time

The computer with specification Intel® Core™ i7-4510U CPU @ 2 GHz calculates the training and testing time of each method. All methods are trained and tested on the same computer with the same data set. The results are shown in Table 8.

As can be seen, the proposed method takes less time to be trained and tested, which is indicated that the proposed method is faster than other approaches.

6 Conclusion

In this paper, a method for online predicting and monitoring the system voltage stability with consideration of overcurrent protection for transmission lines using DE-based SVR has been proposed. The voltage magnitudes and reactive power of the buses are used as inputs to the DE-SVR to estimate the VSI. The performance of the proposed method on the 39 bus New England system is discussed. The results show that the DE-SVR method has advantages over ANFIS and BPNN methods. MSE of DE-SVR is 5.2746e-5 that is indicative of its higher accuracy than other approaches. The correlation index of the proposed method on test data is 0.99948, i.e. there is a strong correlation between the actual values and the predicted ones. Also, in terms of training and testing times, the presented approach is superior to the other methods, with 0.8573 and 0.0062 seconds, respectively.

<table>
<thead>
<tr>
<th>Method</th>
<th>$R$</th>
</tr>
</thead>
<tbody>
<tr>
<td>DE-SVR</td>
<td>0.99948</td>
</tr>
<tr>
<td>ANFIS</td>
<td>0.99736</td>
</tr>
<tr>
<td>BPNN</td>
<td>0.98336</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>Training time [s]</th>
<th>Testing time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>DE-SVR</td>
<td>0.8573</td>
<td>0.0062</td>
</tr>
<tr>
<td>ANFIS</td>
<td>1.1696</td>
<td>0.0084</td>
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Appendix

Table A.1 Optimal Values of TMS and $I_{50}$ for all of the available relays.

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References


Online Voltage Stability Monitoring and Prediction by Using … A. H. Poursaeed and F. Namdari


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