Machine Learning Based Real-Time Monitoring of Long-Term Voltage Stability Using Voltage Stability Indices

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ABSTRACT This article presents a machine learning approach to predict the long-term voltage stability margin as represented by the Loadability Margin (LM). LM is an intuitive and easily understandable indicator of voltage stability. The unique feature of the proposed technique is the use of different Voltage Stability Indices (VSI) proposed in the literature as inputs to an ensemble of machine learning models which predict the LM. The VSIs used are carefully selected to include those based on different principles and computable using real time synchrophasor measurements. In addition, the paper presents a methodology to generate training data under different operational conditions and N-1 contingencies to train the machine learning models. The best machine learning algorithm and the categories of input VSIs are selected through a comparative study. These studies were conducted on the IEEE 14 bus system and IEEE 118 bus system and led to the selection of Random Forest Regression machine learning algorithm, and confirmed the accuracy and robustness of the proposed method. The system was implemented on real time PhasorSmart® synchrophasor application platform and validated using RTDS® real-time simulator. The impact of synchrophasor measurement errors on the proposed technique were also analyzed.

INDEX TERMS Long term voltage stability, voltage stability indices, continuation power flow, synchrophasors, machine learning based voltage stability assessment.

I. INTRODUCTION Modern power systems are operated with smaller stability margins to optimize the utilization of assets, to cater diverse demand patterns and to accommodate ever increasing renewable generation. Therefore they are more prone to various system instabilities, and specifically the voltage instability draws a special attention as the major cause responsible for a number of black-outs occurred in various parts of the world. In many of these events, progressive voltage drops lead to cascaded tripping of transmission lines associated with rotor angle instabilities, eventually collapsing entire networks [1]–[4]. The voltage stability is mainly affected by the available generator reactive power limits, transmission network strength, limits of reactive power compensation devices and load characteristics. However with high renewable penetration levels, the capability limitations of distributed renewable resources and associated electronic controllers also impact the voltage stability margin of the power system [5].

Different approaches used to voltage stability assessment include modal analysis, P-Q and Q-V curve analysis, singular value decomposition, sensitivity analysis, voltage stability indices and continuation power flow [6]. With respect to online voltage stability monitoring, Voltage Stability Indices (VSI) have gained more attention, which can provide quantitative parameters to determine the proximity of voltage instability on a real-time basis [7].

Voltage stability in a Region of Interest (ROI) can be considered as wide area phenomenon. Therefore, the VSIs which are calculated using real-time wide-area measurements...
provides a better insight into the voltage stability of a particular ROI [7]. Synchrophasors provide high-resolution synchronized dynamic data across a wide area of power system [8], [9] enabling a wide range of voltage stability monitoring and controlling potentials for real-time implementations. In literature, many VSIs which could be used to assess wide area voltage stability using synchrophasor measurements have been proposed [7]–[12] and some are detailed in Section II-B. One major drawback of many VSIs proposed in the past literatures from the Operators perspective is that they do not provide enough intuitive information as provided by the offline analysis tools such as P-V curves or continuation power flow for making proper decision. Moreover, these VSIs show different levels of accuracy under different conditions and load models [6]. The practical aspects such as measurement errors and incorrect network topology information can also affect the accuracy of VSIs estimation in different ways and it is difficult to single out one VSI which is more reliable.

Application of computational intelligence and data mining for voltage stability assessment has been investigated in recent years. Online Long Term Voltage Stability (LTVS) assessment using an Artificial Neural Network (ANN) with voltage phasors is proposed in [16]. Decision Tree (DT) based classification approaches are proposed in [13], [14] for assessing system voltage security, while [15] used DT classification for LTVS assessment under small disturbances. To optimize prediction accuracy and speed, Extreme Learning Machine (ELM) technique is introduced for Short Term Voltage Stability (STVS) assessment in [17], [18]. Voltage stability margin prediction via Convolutional Neural Network (CNN) is also proposed in [19]. Support Vector Machine (SVM) based regression has been presented in [20], [21] to assess LTVS. These works have shown a good potential, however, their real-time performance has not been validated and tested thoroughly to improve the real-time operation. There is a rapid progress in machine learning technology and data science, due to continuous availability of increased computational power, and cloud technology in dealing with large power systems [22], [23] and efficient automation tools for power system analysis.

This article investigates a new approach in which the strengths of machine learning and traditional VSI based approaches are combined to compute a familiar and easily interpretable composite VSI suitable for real-time applications. Although machine learning based approaches such as artificial neural networks and support vector machines have been proposed to predict the voltage stability or loadability margin in previous studies, this article introduces two new concepts to improve the accuracy and robustness: (i) use of multiple voltage stability indices as input features instead of homogeneous set of measurements, and (ii) use of multiple machine learning models in an ensemble to enable robust predictions under varying system topology conditions. It will be shown that these two factors can contribute to improve the accuracy and robustness when applying to larger systems. In addition, the paper also presents systematic approaches to select the input features and parameters for the machine learning models. Finally, the proposed method was implemented and demonstrated on a real-time test setup while highlighting and solving some unique problems that would be encountered only in a real-time practical power systems. Reminder of the paper, framework of the approach and the method of development is presented in Section II and III. Numerical results is presented in Sections IV and V, the practical implementation is demonstrated using a test setup consisting of a RTDS® real-time simulator and PhasorSmart®, which is a platform for synchrophasor application development and visualization.

II. PROPOSED SOLUTION AND RELEVANT FUNDAMENTALS

A. LOADABILITY MARGIN (LM)

The voltage stability is commonly explained considering a load (PQ bus) with rest of the power system represented using a Thevenin equivalent circuit as shown in Figure 1(a). The inductive network elements limit the voltage support at the load bus, as the power flow increases [4]. This leads to a point where more power cannot be transferred through the transmission network. This point is defined as the voltage collapse point. The additional power that can be transmitted before reaching the voltage collapse point from the current point of operation is usually referred to as the Voltage Stability Margin or the Loadability Margin (LM), which is typically illustrated using the P-V curve as shown in Figure 1(b). LM is an intuitive and easily understandable indicator of proximity to voltage instability. Operators can be alerted and automatic remedial actions can be initiated when the LM drops below pre-determined critical values.

However, it is impossible to calculate the LM using traditional power flow solution methods since they diverge near the vicinity of the voltage collapse point due to ill conditioned Jacobian matrix. In order to avoid singularity of the Jacobian matrix, the power flow equations can be reformulated by applying a locally parameterized continuation technique. The resulting Continuation Power Flow (CPF) algorithm [3] can be used to trace the P-V curve beyond the voltage collapse point. Although LM is a good indicator, it is difficult to compute the LM in real-time using the CPF for a large network, due to iterative computations involved. Furthermore,
B. MACHINE LEARNING BASED APPROACH FOR COMPUTING LM

It is proposed to express the LM as a function of a set of VSIs which can be computed using synchrophasor measurements on a real-time basis. The particular function that relates the input VSIs to LM can be learned from data using a suitable machine learning technique. It is also proposed to use an ensemble of machine learning models (MLMs), each of which uses a different group of input VSIs or machine learning principle. The underline hypothesis is that by combining models that use VSIs based on different principles, LM can be predicted in a robust manner. The concept is illustrated in Figure 2.

C. MACHINE LEARNING TECHNIQUES

Machine learning techniques are used to approximate the unknown relationship between the multiple input features, VSIs in this case, and the output LM. Supervised machine learning is applied in this work, and the feasibility of the regression techniques listed in Table 1 are examined.

D. VOLTAGE STABILITY INDICES (VSI)

Eleven candidate VSIs which evaluate the voltage stability using diverse principles are considered. Their definitions and the conditions pertaining to the derivation are briefly given in Table 2. Some VSIs assess the voltage stability of a particular load bus considering a Thevenin equivalent as shown.

| TABLE 1. Machine learning techniques. |
|---------------------------------------|
| ML Technique                      | Description |
| Linear Regression (LR) [33]        | LR learns a linear relationship between the input features and the output. Since some of the VSIs shows linear characteristics with the output LM, the LR is considered. |
| Polynomial Regression (PR) [48]    | PR is a type of nonlinear regression that learns a higher degree multivariate polynomial relationship between the input features and the output. |
| Gradient Boost Regression (GBR) [34] | This learning algorithm contains a number of small decision trees which are trained using the pseudo residual of each data instance. Each decision tree is scaled using a learning rate to lower the variance of the combined prediction. |
| Artificial Neural Network Regression (ANR) [35] | In ANN, layers of interconnected neurons are used to obtain an output. Each neuron consists of an activation function and every interconnection has a weight factor determined through learning. |
| Random Forest Regression (RFR) [36] | Random forest consists of N number of decision trees which are trained using random combinations of boost trap data instances. Average of prediction summation of each tree from the forest is considered as the output. |

| TABLE 2. Candidate VSI definition, basis and references. |
|---------------------------------|-----------------|
| VSI definition                  | Basis and reference |
| Voltage Stability Load Index    | Condition to have a real solution for the voltage at bus i of Figure 1(a) [25], $\delta_i$ is the phase angle difference between $V_i$ and $E_{th}$. |
| $VSLI_i = \frac{4[V_i \delta_{th} \cos(\delta_i) - \delta_i^2 \cos(\delta_i)]}{\delta_i^2}$ | |
| Voltage Collapse Proximity Index| Condition at the maximum power transfer of circuit in Figure 1(a) [26]. |
| $VCP_{\text{li}} = V_i \delta_{th} - 0.5P_{th}$ | |
| Voltage Stability Load Bus Index| Condition at the maximum power transfer of circuit in Figure 1(a) [27]. |
| $VSLIB_i = \frac{V_i - V_i \delta_{th}}{|V_i|}$ | |
| S Difference Criterion          | Condition to satisfy at the maximum power transfer by two different local measurements at bus i [28], $\Delta V_{n+1}$ and $\Delta P_{n+1}$ denote the voltage and current phasor difference between $n+1$ and $n$ distinct measurements. |
| $SDC_{i} = \left[1 + \frac{\Delta V_{n+1}^2}{V_i^2} \frac{\Delta P_{n+1}^2}{P_i^2} \right]$ | |
| Bus Voltage Stability Index      | Similar to SDC except for the index a which linearizes the characteristic [29]. |
| $VSI_{bus,i} = \left(1 + \frac{\Delta V_{n+1}^2 + \Delta P_{n+1}^2}{V_i^2 P_i^2} \right)^a$ | |
| Simplified Voltage Stability Index| Condition at the maximum power transfer between bus i and the generator at the lowest relative electrical distance [11], $V_i$ is the source voltage, $V_{th}$ and $V_i$ being the maximum and minimum voltages of the system respectively. |
| $SVSI_i = \frac{V_i - V_{th}}{1 - (V_i - V_{th})^2} V_i$ | |
| Impedance matching Stability Index| At the voltage collapse point the load impedance is equal to the Thevenin equivalent impedance ($Z_{th}$) of circuit in Figure 1(a) [31], This equation is reformulated to calculate using local measurements at bus $i$. |
| $ISI_i = 1 - \frac{|V_{th}^2 + Z_{th}^2|}{|V_{th}|^2}$ | |
| Wide Area Loss Index             | Condition to satisfy the maximum power transfer by consecutive power measurements in a Region of Interest (ROI) [7], $\Delta S_{_{gen}}$ represents the change of generation and power import within the ROI. $\Delta S_{_{loss}}$ represents the change of loss within the ROI. |
| $WALI = \frac{\abs{\text{load gen}} - \text{gen}}{\max(\abs{\text{load gen}})}$ | |
| Voltage Stability Margin         | Available reactive power reserve with respect to the total reactive power capacity of grid connected generators is considered [32]. Injected reactive power is represented by $Q_{th}$ and the total reactive power capacities are represented by $Q_{lim}$. |
| $VSM_i = 1 - \frac{|V_i| E_{th} - V_i \delta_{th}}{2 \cos(\frac{\pi}{4} (\theta_{th} + \phi_{th}))}$ | |
| Reactive Power Reserve Index     | |
in Figure 1(a). To obtain the Thevenin equivalent at the $i^{th}$ bus, the online technique proposed in [24], which uses two different local measurements at bus $i$ for the calculation, can be used.

Placement of phasor measurement units (PMUs) depends on the measurement requirement of each VSI. PMUs are needed at the bus of interest for the local measurement based VSIs such as SDC, ISI, VSI$_{bus}$, VSLI, VSLBI, VCP1, and VSM (see in Table 1 for definitions). In order to determine L and ERPR indices, PMUs are required at all generator buses and at the bus of interest. WALI index can be determined by placing synchrophasor at the boundaries of the region of interest (ROI). Synchrophasors must be placed at all the system buses to determine SVSI index. All these VSIs require positive sequence quantities of the synchrophasor measurements.

III. METHODOLOGY
The development of the proposed voltage stability assessment system consists of several steps, including generating training data, training and evaluation of the machine learning algorithm, and addressing real-time implementation issues. These steps are shown in Figure 3 and described in the following sections.

A. DATA GENERATION FOR MACHINE LEARNING MODEL TRAINING
The approach used for calculating the training data is to perform a continuation power flow, starting from a given operating point. The values of VSIs and the corresponding LM are then calculated using CPF results. The training data set should properly cover the expected region of operation under both normal and contingency situations, and therefore, the base case scenario along with credible N-1 (and N-2, etc. as required) contingency scenarios such as tripping of generator units, transmission lines, fixed shunts, transformers and loads should be taken into account when generating initial operating points for the CPF.

Random deviations are introduced to load and generator settings of the base case and other contingency scenarios in order to have different initial operating points. It is more desirable to generate these random deviations using a normally distributed random variable to follow the natural trend of decrease in the frequency of occurrence with the increase of magnitude of deviation, rather than using a uniformly distributed random variable. Therefore load active and reactive power perturbation are generated using (1) and (2) respectively; where $P_{LO}^{(i)}$ denotes original active power of $i^{th}$ bus and $\epsilon_{PL}^{(i)}(k)$ represents the normally distributed $k^{th}$ random variable with a mean of 0 and a standard deviation of 0.1 for the $i^{th}$ bus. The load reactive power and generator active power deviations are generated in a similar fashion with the same mean and the standard deviation. When computing generator voltage set point deviations using (3), a standard deviation of 0.01 is considered.

\[
\begin{align*}
  P_{L}^{(i)}(k) &= P_{LO}^{(i)} \left\{ 1 + \epsilon_{PL}^{(i)}(k) \right\} \quad (1) \\
  Q_{L}^{(i)}(k) &= Q_{LO}^{(i)} \left\{ 1 + \epsilon_{QL}^{(i)}(k) \right\} \quad (2) \\
  V_{G}^{(i)}(k) &= V_{GO}^{(i)} \left\{ 1 + \epsilon_{VG}^{(i)}(k) \right\} \quad (3)
\end{align*}
\]

All the randomly generated operating points are however not realistic, and their feasibility should be checked by running a power flow. The well-known power system analysis software PSSE® [37] was automated to conduct power flow studies for feasibility check in this work; if the power flow converges before reaching the iteration limit, the operating point is considered feasible.

In order to limit the number of data points, some non-influential contingencies (for voltage stability) are eliminated by considering the value of Contingency Severity Factor (CSF) shown in (4) where $V_{i}$ represents the steady-state voltage of the $i^{th}$ bus after the contingency, $V_{BC}^{i}$ represents the base case voltage and $\Delta V_{i}^{tol}$ denotes the defined voltage deviation tolerance which is equal to 0.025 in this study. If CSF exceeds 1 for at least one of the load buses after the contingency, it is considered as a severer contingency.

\[
CSF_{i} = \frac{|V_{i}| - |V_{BC}^{i}|}{\Delta V_{i}^{tol}} \quad (4)
\]
and the corresponding LM are computed, and saved to a database.

C. MACHINE LEARNING MODEL (MLM) TRAINING

Finally, using the data generated, the machine learning models are trained to predict the LM and are tested to avoid over and under fitting. Predicting the system LM using calculated VSIs requires a multi-variable regression.

The database is split in the ratio of 4:1 as training and testing data. K-fold cross validation, where the training dataset is again split into K consecutive folds and each split is then used once as validation set while the remaining K-1 folds are used for training. The best cross validation split is used to obtain the best generalized estimate. In this study K was defined as 10. Root Mean Square Error (RMSE) and coefficient of multiple determination ($R^2$) are considered as measures to evaluate each MLM.

IV. NUMERICAL RESULTS

A. TEST SYSTEMS

The IEEE 14 bus system and the IEEE 118 bus system are considered for evaluating the proposed voltage stability margin assessment approach. The IEEE 14 bus system Figure 4 consists of 5 generators, 9 load buses with static loads and one fixed shunt. Generators at bus-3, -6 and -8 are operated as synchronous condensers. Analysis of the voltage profile of the system under severer contingency scenarios showed that bus-14 is the most critical bus in terms of the voltage instability for this system. The IEEE 118 bus system consists of 19 generators, 35 synchronous condensers, 56 load buses with static loads and 14 fixed shunts. It was found that bus-45 is the most vulnerable bus for voltage instability in the IEEE 118 test system. The data of the IEEE-14 and -118 bus test systems are available in [39] and [40] respectively.

B. DATA PREPARATION

The bus voltage phasors and the VSI data sets were generated through the approach described in Section III for both test systems. The number of initial operational points considered when creating the training and testing database for the IEEE 14 bus system was 3,196 and that for the IEEE 118 bus system was 5,424. The total number of data points generated through resampling of CPF results were 338,366 and 632,161 respectively for the 14 and 118 bus systems. A CPF program was implemented in MATLAB® with all necessary features and its accuracy was verified. Figure 5 shows an example of a PV curve of a load bus (Bus14) in the IEEE 14 test system. The curve shows the impact of a generator reaching its over-excitation limit as well as the action of an automatic tap changing operations of a transformer. The generator connected to bus-2 reaches its over-excitation limit and changes the trajectory of the voltage profile when the system loads increase gradually as shown in Figure 5. The automatic transformer tap changing operation of transformer between bus-4 and -7 rises the P-V curve and pushes the critical point further as shown in Figure 5.

C. TRAINING FEATURE SELECTION

Four different MLMs that use different categories of input features were developed for identifying the best feature set:

MLM-1: Uses a set of bus voltage magnitudes and phase angles as inputs. The most relevant buses are selected using the recursive feature elimination method [41]. This MLM is similar to the approach proposed in [16] and will be used as a reference model.

MLM-2: Uses all of the VSIs listed in Table-I as input features.

MLM-3: Uses a set of VSIs which are calculated using only the local measurements of the considered bus. The VSIs used in MLM-3 are SDC, ISI, VSI$_{bus}$, VSLI, VSLBI, VCPI$_1$ and VSM.

MLM-4: Uses a set of most relevant VSIs as inputs. The most relevant inputs are selected through Spearman’s rank correlation coefficient method [42], which provides a correlation coefficients equal or close to 1 or -1 when two data sets have close monotonic relationship. When there is no monotonic relationship, the correlation coefficients are close to 0. In this study, only the features with very high...
positive or negative correlation were selected to minimize the number of input features and improve the accuracy. As a rule of thumb used in statistics [49], Spearman’s rank correlation coefficients equal or higher than 0.9 or equal or less than −0.9 are considered as having very high correlation. Therefore, 0.9 was used as the magnitude threshold for feature selection.

Application of recursive feature elimination for the IEEE 14 bus system phasor data resulted in voltage phasors of bus 1, 2, 8, 10 and 14 are the inputs for MLM-1. The corresponding voltage phasors for the MLM-1 for IEEE 118 bus system are from the buses 2, 3, 5, 11, 13, 18, 19, 29, 32, 56, 57, 80, 81, 88 and 95. The Spearman’s rank correlation coefficients heat map for the IEEE 14 bus system, computed with database created in Section II-B, are shown in Figure 6 The indices SVSI, VCPI, VSLBI, VSLI, VSM and L indices can be recognized as the most important features (correlation > 0.9). However correlation between VSM, VSLI, VCPI and VSLBI is 1, hence representing only one of these is sufficient, and VCPI was selected. Thus inputs to MLM-4 are VCPI, SVSI, and L.

### TABLE 3. MLM 1 validation and testing.

| Regression Type | IEEE 14 | IEEE 118 |
|-----------------|---------|----------|
|                 | RMSE    | R²       | RMSE   | R²       |
| LR              | 0.0428  | 0.9047   | 12.643 | 0.1445   |
| Test            | 0.0428  | 0.9065   | 12.569 | 0.1373   |
| PR              | 0.0332  | 0.9455   | 10.514 | 0.4556   |
| Test            | 0.0332  | 0.9437   | 11.003 | 0.3963   |
| GBR             | 0.0472  | 0.9467   | 11.685 | 0.4883   |
| Test            | 0.0473  | 0.9465   | 11.823 | 0.4377   |
| ANN              | 0.0088  | 0.9929   | 4.550  | 0.9292   |
| Test            | 0.0088  | 0.9923   | 57.454 | 0.7128   |
| RFR             | 0.0027  | 0.9999   | 2.265  | 0.9853   |
| Test            | 0.0063  | 0.9981   | 5.296  | 0.9431   |

### TABLE 4. MLM 2 Validation and testing.

| Regression Type | IEEE 14 | IEEE 118 |
|-----------------|---------|----------|
|                 | RMSE    | R²       | RMSE   | R²       |
| LR              | 0.0329  | 0.9425   | 10.552 | 0.0596   |
| Test            | 0.0329  | 0.9456   | 10.455 | 0.0418   |
| PR              | 0.0287  | 0.9563   | 11.573 | 0.0371   |
| Test            | 0.0362  | 0.9304   | 12.037 | 0.0261   |
| GBR             | 0.0463  | 0.9498   | 3.675  | 0.9997   |
| Test            | 0.0463  | 0.9496   | 3.666  | 0.9986   |
| ANN              | 0.0134  | 0.9811   | 8.508  | 0.5863   |
| Test            | 0.0133  | 0.9816   | 1.3e12 | 0.4430   |
| RFR             | 0.0027  | 0.9999   | 0.142  | 0.9999   |
| Test            | 0.0061  | 0.9981   | 0.286  | 0.9993   |

### TABLE 5. MLM 3 validation and testing.

| Regression Type | IEEE 14 | IEEE 118 |
|-----------------|---------|----------|
|                 | RMSE    | R²       | RMSE   | R²       |
| LR              | 0.0370  | 0.9260   | 10.553 | 0.0585   |
| Test            | 0.0371  | 0.9260   | 10.456 | 0.0384   |
| PR              | 0.0358  | 0.9311   | 10.450 | 0.0371   |
| Test            | 0.0391  | 0.9169   | 12.037 | 0.0261   |
| GBR             | 0.0507  | 0.9190   | 10.357 | 0.2155   |
| Test            | 0.0507  | 0.9185   | 10.392 | 0.0746   |
| ANN              | 0.0294  | 0.8527   | 8.506  | 0.5258   |
| Test            | 0.0294  | 0.8525   | 6.5e12 | 0.3634   |
| RFR             | 0.0374  | 0.9992   | 1.881  | 0.9841   |
| Test            | 0.0084  | 0.9963   | 4.216  | 0.9097   |

### TABLE 6. MLM4 validation and testing.

| Regression Type | IEEE 14 | IEEE 118 |
|-----------------|---------|----------|
|                 | RMSE    | R²       | RMSE   | R²       |
| LR              | 0.0421  | 0.8560   | 9.886  | 0.3107   |
| Test            | 0.0422  | 0.8432   | 9.907  | 0.3132   |
| PR              | 0.0358  | 0.9312   | 9.855  | 0.3355   |
| Test            | 0.0356  | 0.9313   | 11.38  | 0.3261   |
| GBR             | 0.0367  | 0.9482   | 9.512  | 0.6242   |
| Test            | 0.0368  | 0.9476   | 9.755  | 0.5409   |
| ANN              | 0.0205  | 0.9279   | 8.505  | 0.5698   |
| Test            | 0.0206  | 0.9274   | 22.82  | 0.4866   |
| RFR             | 0.0049  | 0.9980   | 2.359  | 0.9762   |
| Test            | 0.0104  | 0.9907   | 5.384  | 0.9450   |

Tables 6-7 present the evaluation results, in terms of the root mean square error (RMSE) and the coefficient of multiple determination (R²) values, of each MLM under training and
TABLE 7. Ensemble models with different weights.

| Test System | Weightage ratio | RMSE   | $R^2$  |
|-------------|-----------------|--------|--------|
|              | MLM1: MLM3: MLM4 |        |        |
| IEEE 14     | 1:1:1           | 0.0057 | 0.9983 |
|             | 2:1:1           | 0.0053 | 0.9985 |
|             | 1:2:1           | 0.0061 | 0.9981 |
|             | 1:1:2           | 0.0062 | 0.9980 |
|             | 2:2:1           | 0.0056 | 0.9984 |
|             | 2:1:2           | 0.0056 | 0.9983 |
|             | 1:2:2           | 0.0062 | 0.9980 |
| IEEE 118    | 1:1:1           | 2.8252 | 0.9725 |
|             | 2:1:1           | 2.6935 | 0.9752 |
|             | 1:2:1           | 2.8551 | 0.9717 |
|             | 1:1:2           | 3.0425 | 0.9663 |
|             | 2:2:1           | 2.7216 | 0.9748 |
|             | 2:1:2           | 2.8537 | 0.9713 |
|             | 1:2:2           | 2.9715 | 0.9686 |

D. SENSITIVITY TO SYNCHROPHASOR MEASUREMENT ERRORS

Noise, bias errors, outliers and communication errors can be associated with field measurements. Such errors in synchrophasor measurements can be identified and corrected by using an appropriate data validation method. Detailed investigation of data validation is out of scope of this article but possible methodologies can be found in literature [46]. However, synchrophasor measurement errors cannot be corrected using data validation.

Practical Synchrophasor measurements data may induce errors in the VSIs which could affect the LM prediction. According IEEE standard C37.118-2011 [44] synchrophasors must maintain a total vector error (TVE) less than 1% under steady state conditions. The effect of synchrophasor measurement errors to LM prediction is analyzed by inputting erroneous voltage and current phasors generated by introducing random errors to magnitudes and phase angles such that TVE $\leq 1\%$. The voltage input for the $i^{th}$ bus with measurement errors can be represent as in (5) where $\Delta V_i$ and $\Delta \theta_i$ are the per unit magnitude and angle errors.

$$V_i^* = V_i(1 + \Delta V_i)$$

$$\theta_i^* = \theta_i(1 + \Delta \theta_i)$$

The erroneous current phasors are generated in a similar fashion, and used to calculate the VSIs which are fed to different MLMs trained using RFR algorithm. Fig. 7 compares the RMSE of different MLMs with and without the influence of synchrophasor measurement errors. MLM-3 shows significant prediction error under the influence of synchrophasor measurement errors compared to the others which show relatively lower prediction error even with synchrophasor measurement errors.

E. MACHINE LEARNING MODEL ENSEMBLE

In an MLM ensemble, multiple diverse models are used to predict a common outcome in order to improve the overall performances and robustness. Even though MLM-3 is more amenable for practical implementation, MLM-1 shows higher resilience to synchrophasor measurement errors. MLM-4 on the other hand is more accurate for larger systems. Hence the strengths of different MLMs can be exploited through ensemble modeling. Using the weighted average ensemble method, the final prediction $Y_{en}$ is obtained as denoted in (6) using predictions of individual MLM-s.

$$Y_{en} = \sum_{i \in E} w_i Y_{MLM - i}$$

The training data. It can be observed that these parametric curves will predict the LM with an acceptable accuracy when the system is small; however when the system size increases, the predictions from these generic parametric functions show higher errors and lower co-relation. Therefore generic parametric functions are not very satisfactory for this problem.

ANNR learner shows much higher testing error for MLM-2 and MLM-3. Analysis of the learning curves showed that these two trained ANNR models have high variance in testing error [43], although the training error was decreasing with each iteration. Since RFR shows better accuracy than ANNR model in both IEEE 14 and IEEE 118 bus systems, and exhibit good generalization compared to ANNR, RFR is clearly the most appropriate algorithm for this problem.

When consider the results from both IEEE 14 and 118 bus test systems, predictions from MLM-2 which uses VSIs as the input features shows better overall performance (especially for the larger 118 bus system) than MLM-1 which directly uses voltage phasors, confirming the initial hypothesis. Moreover, MLM-2 achieves this with a lower number of inputs features; MLM-1 of 118 bus system uses 30 features (magnitudes and angles of 15 phasors) while MLM-2 uses 11 input features. Although calculation of 11 features need all of
and calculated VSIs. In this approach RFR models with 20 trees and 100 trees were used for the IEEE 14 and 118 bus systems respectively.

Approach B: This is the LM prediction approach proposed in [16]. The voltage phasors from the critical buses of the power system are the input features. An ANNR model with three hidden layers of 100 neurons was used for IEEE 14 bus system. For the IEEE 118 bus system, an ANNR model seven with a hidden layers of 100 neurons was used.

Approach C: This LM estimation technique is proposed in [20] and uses the real and reactive powers of all buses in the power power system as input features for a \( \varepsilon \)-Support Vector Regression (SVR) model. A \( \varepsilon \)-SVR model with “rbf” kernel, \( C=1 \) and \( \gamma = 0.1 \) was used for the IEEE 14 bus system and a \( \varepsilon \)-SVR model with “rbf” kernel, \( C=1 \) and \( \gamma = 0.15 \) was used for the IEEE 118 bus system. These parameters were chosen using a trial and error approach.

Prediction models in all three approaches were trained and tested using the same set of data (for each power system) containing the same operational conditions and power system contingencies. Table 8 summarizes the testing results for the three approaches for both IEEE 14 and IEEE 118 bus systems. Approach has a lower RMSE and \( R^2 \) compared to the other two Approaches. Although Approaches B and C have close performance for the IEEE 14 bus system, its RMSE is significantly higher for the IEEE 118 bus system. This is despite taking measurements from every bus in the case of Approach C. This comparison highlights the robustness of the approach proposed in this article for larger systems.

**V. REAL-TIME VOLTAGE STABILITY MARGIN PREDICTION TESTBED**

The proposed methodology of predicting LM using local measurement based VSIs and voltage phasors of significant buses was implemented on the real-time synchrophasor application platform PhasorSmart®, and tested using an experimental setup consisting of RTDS®-real-time simulator and a laboratory synchrophasor network. RTDS system simulated the IEEE 14 bus system model in real-time and published the synchrophasor measurements. The loads were gradually increased during the real-time simulation to push the system towards the voltage instability. At each steady state operation condition, VSIs were calculated and fed to the trained RFR model to predict LM. The results were displayed on the Grafana® visualization tool, which is a part of the PhasorSmart platform.

**F. COMPARATIVE EVALUATION**

In order to compare the efficacy of the proposed LM prediction approach, its performance was compared with two somewhat similar approaches proposed in the literature to estimate the loadability margin. These three candidate approaches are compared in terms of the prediction accuracy.

**Approach A:** This is the MLM ensemble proposed in this article. Input features include the critical bus voltage phasors

where \( E \) is the set of models included in the ensemble, and \( w_i \) are the weightages which can be determined either empirically or using a grid search optimization method. LM prediction from an ensemble consisting of MLM-1, MLM-3, and MLM-4 was attempted. The results of the limited grid search conducted to find a good set of weights for MLM-1, MLM-3, and MLM-4 are shown in Table 8. The best weightages, 0.5, 0.25 and 0.25, were selected considering the RMSE and \( R^2 \) for the testing data set of IEEE 14 and IEEE 118 bus systems.

It can be seen that the ensemble model shows better performance than individual MLMs. Figure 8 shows an example case of LM prediction for the IEEE 14 bus system under n-1 contingency (transmission line between bus-2 and -4 out of service). The predictions of different MLMs from the initial operating point to the voltage collapse point are shown. The scenario includes a generator hitting its reactive power limit (when LM \( \approx 0.13 \)). The predictions of the ensemble model are much closer to the target compared to the predictions individual MLMs, some of which clearly deviate at the point of generator reaching its reactive power limit.

**TABLE 8. Comparison of different lm estimation approaches.**

| Test System | Approach | RMSE | \( R^2 \) |
|-------------|----------|------|-----------|
| IEEE 14     | A        | 0.0053 | 0.9985    |
|             | B        | 0.0088 | 0.9964    |
|             | C        | 0.0072 | 0.9963    |
| IEEE 118    | A        | 2.6935 | 0.9752    |
|             | B        | 57.454 | 0.7128    |
|             | C        | 169.62 | 0.9331    |

**FIGURE 8. LM prediction from different MLMs and the model ensemble under the contingency of line tripping between bus 2 and 4 of IEEE 14 bus system.**
as proposed in [46] is a good indicator of transients. MWE is calculated using a moving data window as in (7) where $d_{i,k}$ denotes the decomposed wavelet coefficient of the $i^{th}$ decomposition level of the $k^{th}$ sample of the data window with total of $N$ samples.

$$\text{Mean Wavelet Energy} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \sum_{i=1}^{L(i,k)} (d_{i,k})^2} \quad (7)$$

Calculated MWE of the moving window is compared against a threshold to identify any transients within the window. A data window of 8 measurements ($N=8$) and a threshold of 0.0005 pu was used in this study. When the measurements are free of transients, the local measurement based VSIs are calculated in 128 cycles (2.13s) intervals.

At the beginning, voltage and current phasors are measured if the system is at the steady state. Afterwards if the system changes from one steady state to another steady state the voltages and current phasors will be measured and saved to $V_1$ and $I_1$. Previous $V_1$ and $I_1$ values will be saved to $V_0$ and $I_0$. Hence it avoids calculating VSIs during transients. Therefore LM prediction shows previous LM during the transient and it will update when the transient is over.

C. PREDICTING THE LM VIA TRAINED ML MODEL

Trained RFR model is characterized using six parameter arrays: Tolerance Value ($T_{val}$), Right child ($R_{child}$), Left child ($L_{child}$), node feature ($N_f$), Leaf or non-leaf ($L_n$) and Leaf value ($L_{val}$). Each column of an array contains the values of each decision tree in the random forest, thus the number of columns is equal to the number of decision trees. The program reads these parameters stored in text files during the initialization. VSIs calculated using synchrophasor data are fed to the trained RFR model. The leaf values of the end node of each decision tree in the random forest represent a predicted value of the LM, and the average of all decision tree values is taken as the predicted LM.

D. REAL-TIME MONITORING RESULTS

Figure 10(a) and 10(b) show the voltage profile of bus-14 of the IEEE 14 bus system and LM. Figure 10(b) contain both LM prediction form the ensemble ML model and theoretical LM under different power system operational situations. The simulated scenario start in a steady state, and then goes through a period of gradual load increment. After a brief period of steady operation, the system sees a sudden load increment followed by a sudden load decrement. The last part of the simulation correspond to a three phase fault with consequent tripping of a transmission line.

The loads were increased or decreased by a percentage of scheduled active and reactive powers of the buses. In the case of gradual power increment, active and reactive power was increased by steps of 0.001 pu in every 5s. In the case of sudden power increment 20% of active and reactive power increment at bus 9 was introduced and in the case of sudden power decrement, 10% of power decrement was introduced at the same bus. A three phase fault is applied on the line.
between bus-1 and bus-5 in close proximity to bus-5. The fault was set to persist for 4 cycles before it was cleared by tripping the line. Predicted LM is validated with respect to theoretical LM under all the operational conditions as shown in Figure 10 (b). Theoretical LM is calculated using conventional CPF program. In CPF all loads are gradually increased till the nose point of P-V curve, therefore variation of the theoretical LM during the gradual load increase can be obtained directly from the CPF. In order to calculate the theoretical LM under sudden load increment at bus 9, the conventional CPF is modified to change the load at bus 9 while maintaining a constant load value at other load buses during the change. Line tripping scenario is simulated by performing CPF under the contingency of tripping the line between bus-1 and bus-5. The actual predicted LM values from synchrophasors appears to be slightly conservative, and therefore no major concern.

The spikes in MWE in Figure 10 (c) corresponds to transient changes such as sudden changes in voltage of faults. When MWE is above the defined threshold of 0.0005, the bit value of the transient status changes from 0 to 1, and remains at 1 until the voltage magnitude becomes steady as shown in Figure 10 (d). The predicted LM vary responding to the changes in the load. The voltage of bus-14 drops slightly after removing the line after the fault, but the predicted LM drops significantly, which agree with the correct behavior of the voltage stability monitoring system.

A sample of the system voltage stability monitoring dashboard implemented on PhasorSmart® platform is shown in Figure 11. This provides a simple overview of the current status of the system voltage stability and its trend over a selected time window in the immediate past to the system operator. The visualization is customizable; the window shown in Figure 11. shows real-time voltage magnitudes of the most critical voltage buses with alarms for under and over voltage conditions. Furthermore, LM predictions are visualized for the two most critical buses, bus 14 and bus 8. The set of graphs in the middle shows the recent trend of predicted LM, and bottom right graph shows the recent transient events.

A novel machine learning based approach to predict the long term voltage stability, as represented by the loadability margin, is presented. The proposed method utilizes an ensemble of machine learning based regression models which use selected sets of voltage stability indices as input features for the machine learning models. Machine learning models that use Random Forest regression proved to be robust and accurate irrespective of the system size. Although the loadability margin can be predicted with a random forest regression model that directly uses voltage magnitudes and phase angles with reasonable accuracy, the predictions obtained with voltage stability indices as inputs have a higher accuracy, especially for the larger systems. Furthermore, when an ensemble of machine leaning models that use different input features is used, the accuracy and the robustness can be increased under both normal operating conditions and N-1 contingencies. With the ensemble approach, the correlation between the predicted and actual loadability margin could be improved to 99.7% and 97.6% for the IEEE 14 bus and 118 bus test cases respectively. When compared to two previously proposed approaches, the ensemble approach proposed in this article could predict LM more accurately, especially for large power systems. The practicality of the proposed method was demonstrated by implementing the scheme on PhasorSmart® real-time synchrophasor based platform and validating it on RTDS® real-time simulator. However, some future work such as managing transients, and PMU data quality issues needs to be implemented to improve the performance of the proposed technique for real-time implementation. Opportunities also exist for further improvements such as employing of methods to adapt for seasonal loading conditions and online training using real-time measurements.
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