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Real-time Implementation and Performance Analysis of a Machine Learning Based Voltage Stability Monitoring System

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SUMMARY

The idea of real-time long-term voltage stability monitoring has been actively investigated because there were several blackouts at various parts of the world due to the long-term voltage instability . Use of Voltage Stability Indices (VSIs) is a widely considered real-time voltage stability assessing method. However, VSIs show different levels of accuracy under varing power system operating conditions and contingencies. Therefore it becomes difficult for the system operators to differentiate voltage instability conditions from normal operating conditions based on any single index.

In this study, real-time implementation of a previously proposed machine learning based voltage stability monitoring algorithm is considered. The unique feature of the proposed approach is the use of different VSIs proposed in the literature as inputs to an ensemble of Machine Learning Models (MLMs). The output of this algorithm is the Loadability Margin (LM), which is a direct representation of proximity to long-term voltage stability. This voltage stability monitoring system was implemented on PhasorSmart® synchrophasor application platform, including a user friendly dashboard that visualizes the monitoring results. The system is tested using the IEEE 14-bus system and phasor measurement units simulated on RTDS® real-time simulator. The main objective of this study is to analyse the practical aspects of the real-time implementation. Two approaches to mitigate the effects of transient measurements, namely the wavelet transform and the moving average filters, is compared. The impact of synchrophasor transmission errors on the accuracy of LM prediction is analysed. The experimental studies showed that the wavelet based transient mitigation scheme provides more smooth and reliable LM predictions and that the system can tolerate about 32 consecutive erroneous measurements received at a rate of 30 frames per second, with less than 2.5% average prediction error.

KEYWORDS

Dynamic Security Assessment (DSA), Voltage Stability Monitoring (LM), Loadability Margin (LM), Machine Learning Models (MLM), Voltage Stability Indices (VSI), Real-time digital simulator, Phasor Measurement Unit (PMU)

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1. INTRODUCTION

Modern Power systems are more likely to be subjected to various system instabilities because they are operated with tighter margins of stability. Dynamic nature of power systems and the advanced control algorithms of equipment makes the job of power system operators challenging. In order to address the system security issues, power utilities and system operators have implemented on-line Dynamic Security Assessment (DSA) and real-time stability monitoring systems [1][2][3][4]. Real-time stability monitoring systems are typically implemented in the centralized control centers. These systems collect wide area measurements, analyse and raise relevant alarms when the system security issues are detected so that the system operators can initiate remedial actions.

Voltage instability is one of the important phenomena monitored using real-time stability monitoring systems, and several real-time Voltage Stability Monitoring (VSM) systems are reported to be practically in use [5][6] while several VSM products are commercially available [5][7]. The real-time VSM systems typically use different Voltage Stability Indices (VSIs) to indicate the voltage stability. However, one major drawback of some VSIs is that although they reach some critical value at the voltage collapse point, they do not provide intuitive information on the voltage stability margin [8]. Furthermore, VSM systems show different levels of accuracy under different system conditions and the practical aspects such as the effect of measurement errors and missing information on computation of the VSIs need to be properly understood before deploying them in practical systems.

This paper describes real-time implementation of a VSM system which monitors the long-term voltage stability based on the machine learning based approach proposed in [9] and investigates its performance. This VSM system assess the voltage stability margin as represented by the Loadability Margin (LM) of the power system. The unique feature of the proposed approach is the use of different VSIs proposed in the literature as inputs to an ensemble of Machine Learning Models (MLMs) which are trained offline. While [9] presented the methodology, validation and a demonstration of basic real time operation of a new VSM system, this paper investigates some practical issues such as handling of VSI outliers during system transients, communication errors and their effects on the prediction of LM.

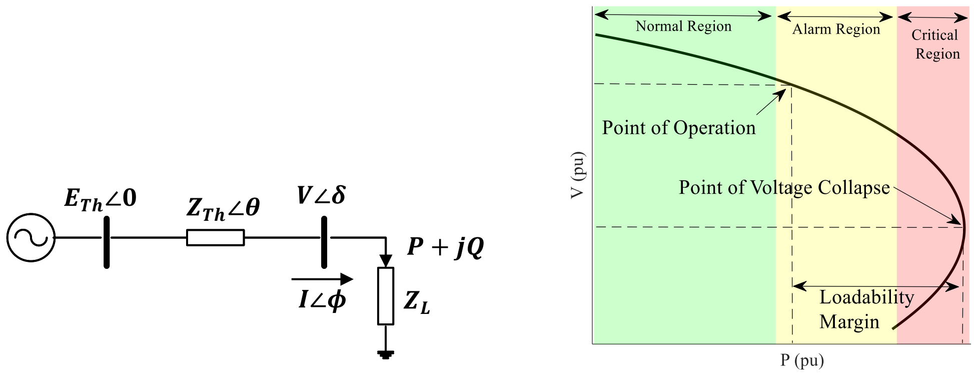
The remainder of the paper is organized as following: The proposed method of voltage stability margin prediction is briefly described in Section II. Then in Section III, the experimental implementation of the proposed real-time VSM system is presented along with the setup used for the performance analysis of the VSM system . The test system and the Phasor Measurement Unit (PMU) placement of the considered power system is explained. Section IV presents and discusses the results followed by the salient conclusions.

2. VOLTAGE STABILITY MONITORING TECHNIQUE

The voltage stability of a power system can be explained considering a simplified equivalent circuit as shown in

Figure **1**.(a) and the P-V curve as shown in

Figure **1**.(b). As the power flow increases, the inductive elements in the transmission network consumes increasing amount of reactive power and limit the voltage support at the load bus [4], leading to a maximum power transfer point, also known as the nose point or the point of voltage collapse. The additional power that can be transmitted before reaching the voltage collapse point from the current point of operation is defined as the Loadability Margin (LM). Although LM is an intuitive and easily understandable indicator of proximity to voltage instability, the iterative computations involved in tracing the P-V curve using the Continuation Power Flow (CPF) limits the use of theoretical calculation of LM in real-time VSM applications, specially for large networks. Therefore, an alternative approach based on machine learning is proposed in [9] to predict the LM in real-time using synchrophasor measurements.



(a) (b)

Figure 1(a) Thevenin equivalent circuit of the network at bus, (b) P-V curve at bus

2.1 Machine Learning Models Based Loadability Margin Prediction Scheme

The concept of VSM system proposed in [9] is shown in Figure 2, and it uses a set of pre-trained MLMs to predict the voltage stability margin in terms of the LM in real-time. The synchrophasor measurements are obtained from specific locations of the power system after analysing the relevance of each measurement to predict the LM as described in [9]. These input measurements are validated and conditioned to avoid any bad data. Afterwards, the transient measurements that occur due to system disturbances are filtered and smoothed before calculating the desired VSIs, as transients can cause unrealistic fluctuations in VSIs. After calculating the VSIs they are fed to the trained MLMs. The voltage phasors are fed directly to some MLMs. The predictions of the MLMs are aggregated to obtain the final value of LM at the current operating point. Each MLM is trained off-line considering different operating conditions, including n-1 contingencies, using different sets of calculated VSIs and voltage phasors.

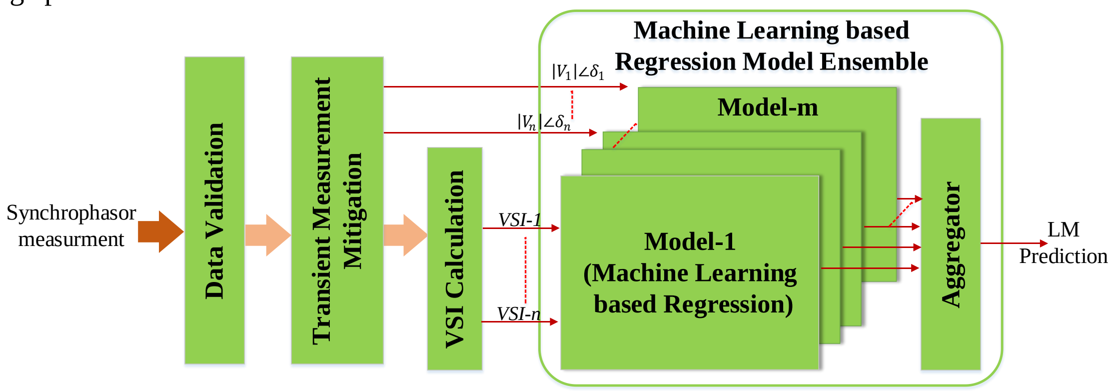


Figure 2. Proposed approach for real-time VSM [9]

2.2 Data Validation

When using real-time synchrophasor measurements in a critical application, it is very important to check the validity of the incoming data, because expected outcomes of the application will not be obtained if invalid data is used. Invalid data is associated with data frame errors which occur due to various reasons. Data corruption error is a common PMU data error where the message frame size, CRC bit or message structure may differ from the validation data provided in the frame itself. The main causes of this type of errors are routing errors, communication bit errors and tampering and spoofing. Loss data from one or several PMUs and signal loss from PMUs is another type of general error, which mainly occur due to communication hardware failures, PMU hardware or algorithm failure or power loss to the PMUs. Identifying these erroneous data frames is the main task of the data validation block. In the proposed VSM system architecture ePDC (Virtual PDC) is responsible for the data validation and condition, it identifies the bad data and convert them to ‘NaN’ which are basically the discarded data points [16].

2.3. Mitigation of the Impact of Transients

When the power systems are subjected to a significant disturbance such as a fault, sudden load drop or reconnection, tripping of a line or a capacitor bank, and energization of a power transformer or a large motor, power systems variables go through transient variations. These transient measurements results in highly unrealistic VSIs values due to sudden changes in the measured voltage magnitudes and phase angles. The accuracy of PMU measurements during the transients cannot be guaranteed and is not defined in the standards [9]. On the other hand, the long term voltage stability is a slower phenomenon and calculation of VSIs and LM during the transient periods is meaningless. Therefore, transient periods must be detected and the process of calculating LM should be suspended until the system approaches a steady state or otherwise the measurements should be smoothen over a suitable time window before using for VSI calculations. In addition, many VSIs require voltage and current phasors taken at two different steady states, and the transient detection can also be used to recognize the possible occurrence of new steady states. In this study two methods to mitigate the effect of system transients towards LM prediction is analysed.

2.3.1. Wavelet Analysis Method

This is the method proposed in [9] for detecting transients. Wavelet analysis is an efficient technique to detect the transient changes which decomposes a signal into basis functions that are localized in scale and time. In order to detect transients and suspend the measurements, it is proposed to apply online Discrete Wavelet Transform (DWT) implemented using Mallat's tree algorithm [10]. Three decomposition levels with "Haar" mother wavelet applied on synchrophasors voltage magnitudes measured at 30 frames per second found to be sufficient. Mean Wavelet Energy (MWE) computed using detail wavelet coefficients as proposed in [11] is a good indicator of transients. MWE is calculated using a moving data window as in (1) 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.

$$MWE = \sqrt{\frac{1}{N}\sum_{k}^{N}\sum_{i}^{L}(d_{i,k})^2} \tag{1}$$

The calculated MWE of the moving window is compared against a defined threshold to identify any transients within the window. A data window of 8 measurements (N=8) and a threshold of 0.0005 pu has been proposed in [9]. When the measurements are free of transients, the local measurement based VSIs are calculated in 128 cycles (2.13s) intervals.

In order to calculate VSIs that need two distinct operating points, two measurement arrays are maintained, (V_0 and I_0) and (V_1 and I_1). 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 passing through a transient state, the new steady state voltages and current phasors are measured and saved to V_1 and I_1. The previous V_1 and I_1 values are saved to V_0 and I_0. Hence, it avoids calculating VSIs during transients. Therefore, LM prediction shows previous LM prediction during the transient and it will update to the new value when the transient is over.

2.3.2. Moving Average Filtering Method

Long-term voltage stability is a slow phenomenon therefore a moving average filter with a defined window size can be considered to mitigate the transient nature in the measurements. This filter buffers the samples in the considered window and outputs the average value of the data in the buffer. A suitably selected window length can be used to avoid short-term system transients. The moving average filter equation is given in (2) where x referred to the time series measurements up to time t and $y[t]$ is the output of the filter at time t. N is the moving window size and Δt is the sampling interval, in this case the time between two synchrophasor measurements, or the reciprocal of the frame rate.

$$y[t] = \frac{1}{N}\sum_{i=0}^{N-1} x[t - i\Delta t] \tag{2}$$

In this method, a window width of 5s or a buffer of 150 samples (@ 30 fps synchrophasor measurement rate) is considered. This window length can be shortened if required, but 5s window was found to be satisfactory. In order to detect different steady state operating points when using this method, the output of every moving average window is compared with the output of the previous window value. If the difference is higher than a defined threshold, the current voltage and current phasors are saved to V_1 and I_1 arrays. The previous V_1 and I_1 values are saved to V_0 and I_0 arrays. A threshold value of 0.01 pu is suggested.

2.3.3. Machine Learning Models

Three MLMs have been used to predict the LM of the proposed VSM system. LM prediction from these MLMs are aggregated to obtain the final LM prediction. Each of these MLMs requires different inputs. First MLM uses the most relevant bus voltage magnitudes and phase angles as inputs. These features are selected using the recursive feature elimination method. Second MLM uses a set of VSIs which are calculated using only the local measurements of the considered bus. The third MLM uses a set of most relevant VSIs as inputs. The most relevant inputs are selected through Spearman's rank correlation coefficient method. Feature selection methods are further explained in [9].

3. EXPERIMENTAL SETUP

3.1 Test Power System

The IEEE 14 bus system is considered for evaluating the proposed voltage stability margin assessment approach. This small system is selected as it need to be implemented on a real-time simulator, and it is adequate to demonstrate the implementability of the proposed VSM system which could be extended to monitor the voltage stability of a larger system. Analysis of the voltage profile and the VSIs of the system under severer contingency scenarios showed that bus-14,8 , 2 and 1 are the most critical buses in terms of the voltage instability of this system. Therefore, PMUs are placed at those buses of the model used for real-time simulations. The data of the IEEE -14 test systems is available in [12].

3.2 Laboratory Setup

The proposed real-time VSM scheme is tested experimentally using real-time data from a real-time digital simulator. The results obtained using the experimental setup is cross validated using the theoretical results obtained through the CPF. A schematic of the system architecture (hardware and software) of the experimental setup is shown in Figure 3. The real-time simulator consisted of a RTDS® rack containing PB5 processor cards, a GTNET_communication card with PMU configuration, and a GTSYNC card connected to a SEL® 2407 satellite clock. A local area network (implemented using a RuggedCom™ RSG2288 utility grade Ethernet switch) connects the GTNET output with a PC that runs the PhasorSmart platform.

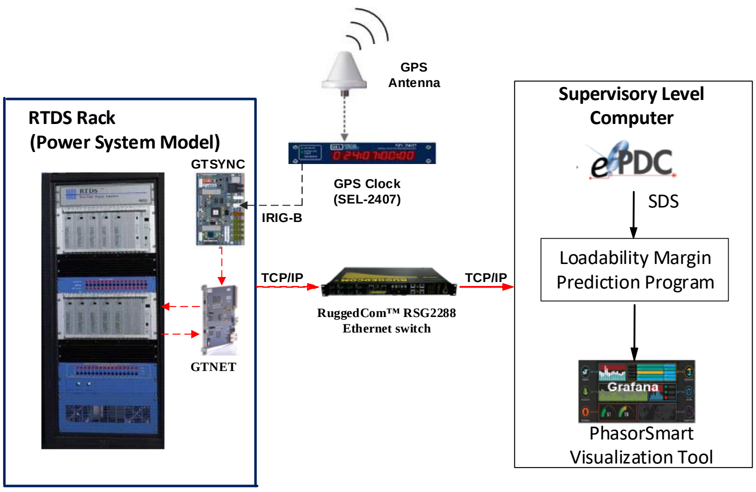


Figure 3. Real-time VSM laboratory setup [9]

3.3 Real-time VSM System Architecture

The VSM system described in Section 2.2 is implementation on PhasorSmart® software platform [15]. Software architecture of the synchrophasor application program used to predict LM in real-time consists of three main modules: ePDC virtual Phasor Data Concentrator (PDC), Synchronous Data Server (SDS) and C++ application program which implements the transient measurement mitigation, VSI calculation and LM estimation using the trained MLMs using the data extracted from SDS. A web based voltage stability monitoring dash-board was implemented using Grafana visualization tool. It acts as the user interface, which provides the operator voltage stability information in a user-friendly manner along with the alarms that activate when the system become closer to the verge of voltage stability.

3.4 Experimental Performance analysis setup

In this study, performance of two transient measurement mitigation methods is analysed. Furthermore, an analysis is carried out to study the effect of PMU data errors towards the final LM prediction. Therefore, the real-time VSM system setup is modified to perform the aforementioned analyses. Since the transient measurement mitigation performance has to be analysed using the same PMU data stream, required PMU data streams published from RTDS test case are recorded (archived) under following scenarios.

- Gradual load increment: Active and reactive power loads were increased by steps of 0.001 pu in every 5s
- Sudden power decrement: 20 % of active and reactive power decrement at bus 9 was introduced
- Sudden power increment: 10 % of power increment was introduced at the same bus
- Three phase fault: Fault is applied on the line between bus-1 and bus-5 in close proximity to bus-5 and the fault was set to persist for 4 cycles before it was cleared by tripping the line.
- Voltage collapse : Gradually increase the active and reactive power loads until voltage collapse.

These archived PMU data streams are replayed using ePDS™ platform as shown in Figure 4. ePDS™ is a PMU simulator which runs on a local PC and replays recorded PMU data frames. In this setup, these data frames are fed to the ePDC instead of PMU data coming from the RTDS simulator. LM prediction were obtained for under each transient measurement mitigation method for analysing.

The ePDS™ platform is capable of injecting PMU data frames with different errors. Therefore, the same experimental setup was used to analyse the effect of PMU data frame errors towards the LM prediction. This analysis was done in steady state, Therefore, test system was simulated at an operating point where the LM was 0.2889 pu and the PMU data streams were archived. Similar to the previous procedure, PMU streams were replayed, but with different amounts of erroneous PMU data frames were injected along with good data. In this study, the errors which were taken in to consideration are data corruption errors (ex: header errors, frame size errors, etc.) and packet loss errors. With ePDS, it is possible to inject different number of samples with above mentioned errors to the replaying PMU data stream. Varying numbers of errorneous measurments, 4,8,16 and 32, were injected to analyse the impact on the LM prediction accuracy. Furthermore, Wavelet based transient measurement mitigation scheme was used to mitigate transient measurements in this part of the experiment.

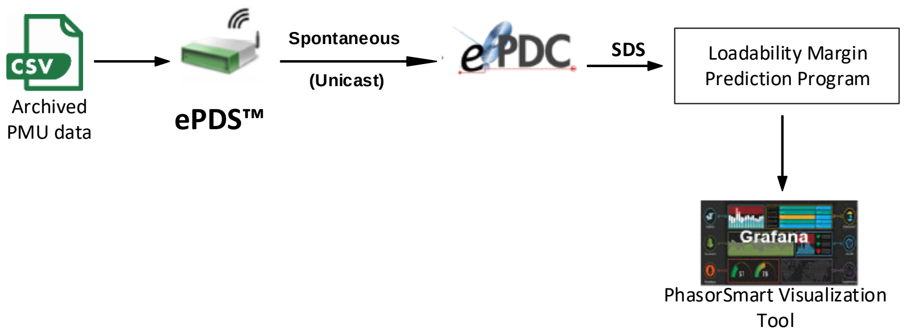


Figure 4.Experimental setup to mimic synchrophasor data errors

4. PERFORMANCE EVLAUTION OF VSM SYSTEM

Figure 5(a) and Figure 5(b) show the voltage profile of bus-14 of the IEEE 14 bus test system. Figure 5(b) contain LM prediction form the ensemble ML model using wavelet based and moving average based transient measurement mitigation methods. Results from both of these methods are plotted under different power system operational situations explained in Section 3.4.

The predicted LM values using wavelet base transient measurement mitigation method appears to be providing the prediction instantaneously where as in moving average filter method prediction approaches to the desired value in steps . Hovever, wavelet method show a lag in LM prediction , this is because wavelet method compute the prediction after the transient is fully decayed.

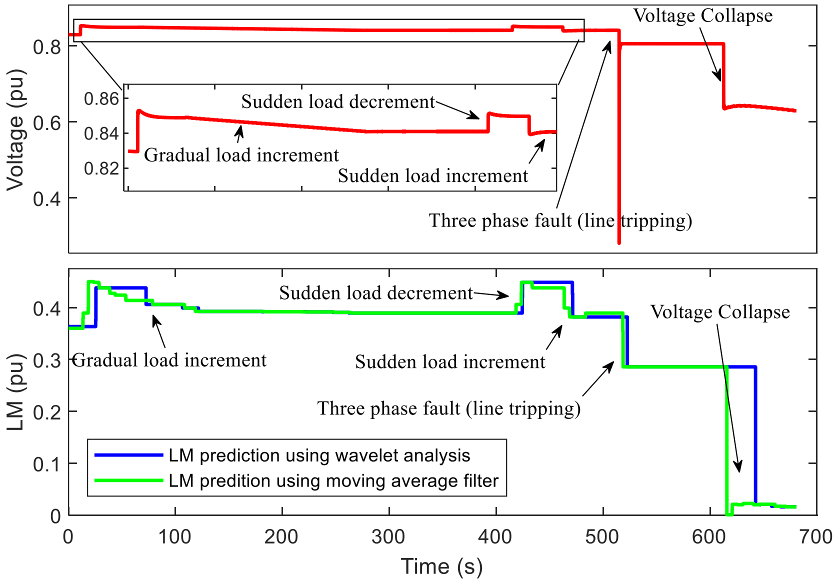


Figure 5. (a) Voltage profile of bus-14 of the IEEE 14 bus system (b) LM prediction using different transient measurement mitigation methods

The experiment to examine the effect of PMU data errors to LM prediction is carried out. In order to generalize the results, each LM prediction is compared with respect to the desired LM and calculated the percentage error from (3). LM_0 and LM_p correspond to the desired LM and the predicted LM under erroneous conditions respectively. The desired LM was obtained from real-time experimental setup at steady state without introducing any errors.

$$Percentage\ error = \frac{LM_0 - LM_p}{LM_0} \times 100\% \tag{3}$$

In this study synchrophasor measurement errors weren't considered because that has been studied in [9]. Results obtained under each case are shown in Figure 6. Different error types show various error percentages. The data corruption errors were introduced at random instances. In packet-loss scenarios, a number of consecutive samples are missed. This explains the higher error percentage under packet loss over the data corruption errors. It can be also observed that when the number of erroneous samples increases, the prediction accuracy decreases.

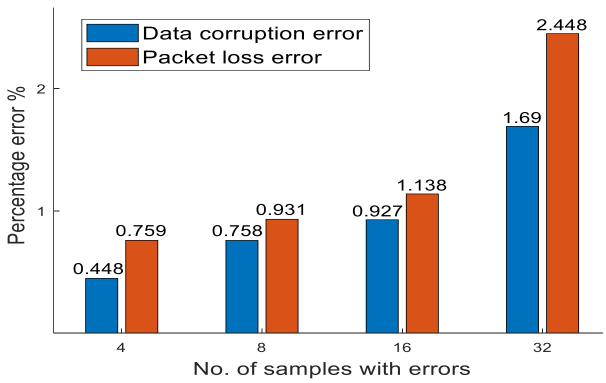


Figure 6. Percentage error of LM prediction under data errors

5. CONCLUSION

This paper investigated the real-time performance of a voltage stability monitoring system. It compared two methods to deal with transient conditions. From the studies carried out, it was observed that wavelet based transient mitigation scheme provide instantaneous and reliable LM prediction than the moving average scheme. Furthermore, when the number of samples with data errors increases, the accuracy of LM prediction decreases. The average errors up to 2.5% were observed, when the 32 consecutive erroneous measurements are received. This highlights the importance of providing a solid communication network to ensure dependable voltage stability margin predictions.

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