Synchrophasor-Based Online Transient Stability Assessment Using Regression Models

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ABSTRACT

An online post-fault transient stability assessment method is proposed in this study using synchrophasor or PMU measurements. Initially, a post-fault multimachine system is converted into a suitable one machine infinite bus (OMIB) system using the single machine equivalent (SIME) method. Thus, the P_a-δ trajectory obtained through the OMIB system enabled a normalized transient stability index to be calculated offline. By using synchrophasor measurements before and during the fault as inputs, the regression model can be trained offline to predict the normalized stability margins. Following a fault, the synchrophasor measurements are used as input to this trained model for online stability margin prediction. If the predicted margin is negative, then the post-fault power system is indicated to be unstable. Alternatively, positive values for the predicted margin identify the system as stable. The proposed assessment method is verified using the New England (NE) 39 bus test system. The results obtained are then compared with offline simulations.

Keywords: Regression Analysis, Single Machine Equivalent, Synchrophasor Measurements, Transient Stability Margin, Transient Stability Prediction

1. INTRODUCTION

An online transient stability assessment is very important following a large disturbance such as a three-phase fault, sudden loss of a large load or large generator, etc. Even though the occurrence of transient instability is rare, its detection and mitigation using suitable control action are crucial. In this regard, the online assessment of transient stability is essential for today's large, interconnected power systems. The transient stability associated with power systems reflects the ability of that system to become synchronous after a huge disturbance [1–3]. The occurrence of transient instability may lead to cascading failures or even block-outs. To avoid such problems, it is necessary to maintain and operate with sufficient stability margins. This is possible only when the operator has clear information about the present operating stability margin. In this paper, a fast online method is proposed for the prediction of a normalized transient stability margin using synchrophasor measurements.

Time domain simulation (TDS) is a practical method for accurate assessment of complicated power systems with detailed component modeling. However, using TDS for online stability assessment poses difficulty since it involves high dimensionality and nonlinearity, leading to lengthy computation time. Direct or transient energy function (TEF) methods [4–6] overcome the heavy computational burden involved with the TDS method but encounter the problem of limited scalability, while their conservativeness makes them less suitable for online applications. Hybrid methods using a combination of both TDS and TEF [7–12] improve the performance of the TEF, but errors resulting from the application of different models and contingencies still remain. Another category of transient stability assessment methods is machine learning, such as fuzzy-based systems, support vector machines (SVM), decision trees (DT), artificial neural networks (ANN), extreme learning machines (ELM), etc. With numerous offline training cases, these methods can judge the stability of the system with good precision.

With the help of synchrophasor measurements, these machine learning methods are becoming more useful in online applications since they are faster and more accurate compared to other approaches. In [13], a model-free method with PMU measurements and an online ensemble of successive learning machines is suggested for post-fault transient stability prediction. Initially, the n-machine system is converted into an OMIB system and the OMIB-ω trajectory transient stability then assessed. In the work presented in [14], the PMU measurements from generator buses are used for estimation of the post-fault transient stability margin by the TEF technique. In [15], a data mining and PMU measurement-based two-stage method is proposed for the online dynamic signature identification of a power system. Initially using a constructed binary training database, all contingent rotor angles are predicted using decision trees (DT). If the system is found to be unstable, the use of predictors as a multiclass classifier identifies the dynamic behavior of the unstable case.

Utilizing a soft computing method by means of a decision tree ensemble with PMU based data, an online dynamic security assessment (DSA) scheme is described in [16]. Using the random subspace method, multiple

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small decision trees are initially trained offline. Then, close to real time, the performance of these small decision trees is rechecked with new cases. For missing PMU data, feasible small decision trees are recognized, and a boosting algorithm utilized to calculate the voting weights. The security classification conclusion for online DSA is identified through the weighted voting of feasible small decision trees. A novel online transient stability estimation system is presented in [17], based on only 10–12 samples of fault data collected by geographically distributed PMUs without resolving the widespread electromechanical dynamics. Thus, the collected PMU data is synchronized and evaluated on a computing platform to forecast the generator trajectories to assess the stability of the system.

In [18], a regression tree approach is presented for power system stability margin prediction and the detection of a forthcoming system event. Synchronized voltage and current phasors are used as input features for the regression tree (RT) to predict the voltage and oscillatory stability margins. A PMU and DT-based online DSA system for large, interconnected power systems is proposed in [19]. Here, the DTs are periodically updated offline to provide the security status and online corrective plans based on real-time measurements. Taking the sample PMU bus voltage phasor, the instability mode prediction and transient stability assessment process is described using convolution neural networks [20]. The prediction involved observing a short window after the disturbance. In [21], an approach for the prediction of both rotor and angle small-signal stability is proposed, using an online deep learning technique. The deep learning technique employed uses the measurements of the voltage phasor collected across the system for training the online model for stability prediction. [22] present an algorithm for online out-of-step prediction using the acceleration power and rotor speed deviation of the generator by fitting ellipses. A unique measurement and simulation-based mixed method for TSA and emergency control scheme is discussed in [23]. Using the difference between the offline and online simulation trajectory of a corresponding single machine infinite bus system, a deviation energy index is defined for fast online transient stability assessment.

In [24] provides a snapshot ensemble of a long and short-term memory (LSTM) network-based two-stage power system TSA method. The regressor is used to predict the transient stability margin, which offers a quantitative assessment of the transient stability risk. Various aspects of power system instability prediction are addressed in [25], including the principles, methodology, accuracy, and practical considerations for implementation. The relevant papers are reviewed and classified with the benefits and drawbacks of each underlined. Two PMUNET variants, DCDL and CDL, have been developed for anomaly detection of drifting synchrophasor data streams in the presence of DERs [26]. To identify distribution changes over streaming PMU data, this study presents a data drift detection algorithm (DCDA) with a DCDL version. While in CDL, the model uses blind adaptation algorithms to continually adapt to data drift in the PMU data streams.

In [27] provides a comprehensive overview of synchrophasor technology (ST), including its principles and applications. The review covers all of the current applications of ST in transmission and distribution networks. Various approaches for optimal PMU placement (OPP) have been discussed. A new instance-transfer approach [28], based on a compression and matching strategy, is proposed to achieve high sample collecting efficiency following operation mode shift, whereby useful previous samples are inherited directly to create a new sample. In addition, a hybrid model is proposed to ensure rationality in sample similarity comparison and selection by introducing the highly important aspects of analytical models into data-driven methods. Meanwhile, in the hybrid model, a data-driven method is used to provide fast error correction in analytical models, allowing for quick and accurate post-disturbance transient stability assessment. In [29], a new method is presented for predicting transient instability and the number of generators that must be tripped to keep the remaining generators synchronized in real time using local measurements. The method allows the strength of the power angle characteristic to be assessed immediately following fault clearance for both regular and extreme contingency situations using merely the locally measurable data available in the considered substation.

In this current study, the single machine equivalent (SIME) method is proposed to transform a multimachine system into its equivalent OMIB. Using the accelerating and decelerating area of the equivalent OMIB P_a-δ trajectory, a new normalized stability margin is then defined. Along with the stability status, the stability margin also provides the contingency severity information. Regression models are developed and trained to predict the stability margin online. The simulations are carried out using MATLAB-based simulation packages [30–32].

2. SINGLE MACHINE EQUIVALENT (SIME) METHOD

2.1 Basics

The SIME method [7] is a combination of the TDS and equal area criterion. Irrespective of its complexity, the system components can be modeled with different order models. This method can also be used to assess the system for its stability margin, contingency ranking or filtering, and critical clearing time (CCT). In the SIME method, the multimachine system is reduced into the equivalent OMIB through the observation of rotor angles derived from TDS. At each instant, the generator post-fault rotor angles are observed and categorized into two groups. These critical machines (CMs) swing together, deviating from the reference, potentially causing the post-fault power system to become unstable. The remaining machines swinging together are labeled non-critical machines (NMs).

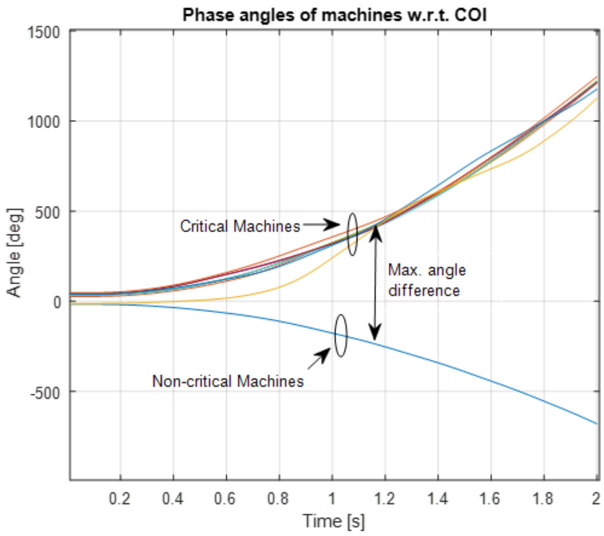

***Fig. 1**: Grouping of machines.*

2.2 Equivalent OMIB Formulation

Using the post-fault rotor angles during each step of the TDS, all machines are divided into two groups and switched by the OMIB equivalent according to the following steps.

1. At every time step, initially the speed and rotor angles are transformed to the center-of-inertia (COI) frame of reference.

$$\delta_{i\mathrm{COI}} = \delta_i - \delta_0 \tag{1}$$

$$\omega_{i\mathrm{COI}} = \omega_i - \omega_0 \tag{2}$$

where

$$\delta_0 = \frac{1}{M_T}\sum_{i=1}^{n} M_i\delta_i;$$

$$\omega_0 = \frac{1}{M_T}\sum_{i=1}^{n} M_i\omega_i;$$

$$M_i = \frac{2H_i}{2\pi f};$$

$$M_T = \sum_{i=1}^{n} M_i;$$

δ_i is the rotor angle of the i^{th} machine;

ω_i is the angular velocity of the i^{th} machine;

$\delta_{i\mathrm{COI}}$ is the rotor angle of the i^{th} machine in the COI frame;

$\omega_{i\mathrm{COI}}$ is the angular velocity of the i^{th} machine in the COI frame;

H_i is the inertia constant of the i^{th} machine in MWs/MVA;

M_i is the inertia coefficient of the i^{th} machine.

2. These rotor angles are sorted in increasing order and divided into two clusters according to the highest difference between two adjacent generator rotor angles, as shown in Fig. 1. These two clusters are labeled critical and non-critical.
3. The rotor angles and speed corresponding to these groups are tabulated as follows;
Critical group (C) rotor angles and speed:

$$\delta_C(t) = \frac{1}{M_C}\sum_{k\in C} M_k\delta_k(t) \tag{3}$$

$$\omega_C(t) = \frac{1}{M_C}\sum_{k\in C} M_k\omega_k(t) \tag{4}$$

Non-critical (N) rotor angles and speed:

$$\delta_N(t) = \frac{1}{M_N}\sum_{j\in N} M_j\delta_j(t) \tag{5}$$

$$\omega_N(t) = \frac{1}{M_N}\sum_{j\in N} M_j\omega_j(t) \tag{6}$$

4. The equivalent OMIB parameters of the multimachine system are obtained as:

$$\delta_{\mathrm{OMIB}} = \delta_C(t) - \delta_N(t) \tag{7}$$

$$\omega_{\mathrm{OMIB}} = \omega_C(t) - \omega_N(t) \tag{8}$$

Mechanical, electrical, and acceleration power:

$$P_m(t) = M\left(\frac{1}{M_C}\sum_{k\in C} P_{mk}(t) - \frac{1}{M_N}\sum_{j\in N} P_{mj}(t)\right) \tag{9}$$

$$P_e(t) = M\left(\frac{1}{M_C}\sum_{k\in C} P_{ek}(t) - \frac{1}{M_N}\sum_{j\in N} P_{ej}(t)\right) \tag{10}$$

$$P_a(t) = P_m(t) - P_e(t) \tag{11}$$

where $M_C = \sum_{k\in C} M_k$, $M_N = \sum_{j\in N} M_j$, and $M = M_C M_N/(M_C + M_N)$.

The stability criteria for a stable case are identified when the OMIB P_a-δ trajectory reaches a return angle of δ_r ($\delta_r < \delta_u$), as shown in Fig. 2. This can also be easily identified from the OMIB omega trajectory when $\omega = 0$, at time $t_r = 0$ as in Fig. 3.

$$\omega(t_r) = 0 \qquad P_a(t_r) = P_{ar} \qquad \eta_{st} = \int_{\delta_r}^{\delta_u} |P_a|\, d\delta \tag{12}$$

Similarly, the stability criteria for an unstable case are identified when the OMIB P_a-δ trajectory reaches an

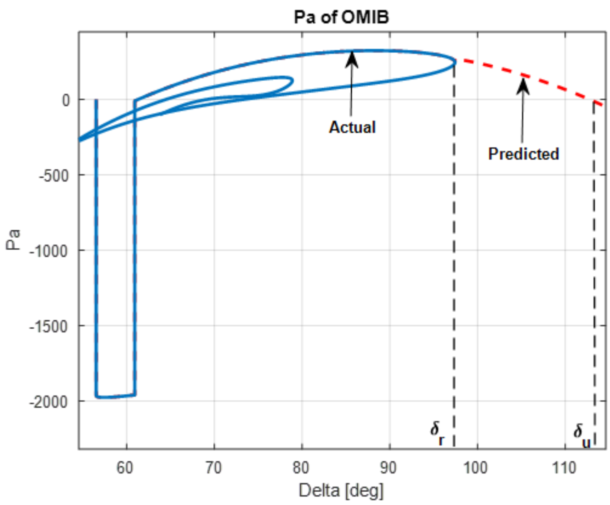

***Fig. 2**: OMIB P_a-δ trajectory for the stable case.*

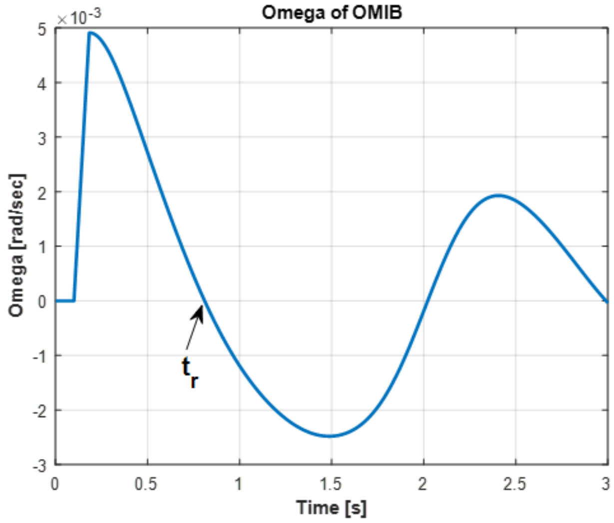

***Fig. 3**: OMIB ω trajectory for the stable case.*

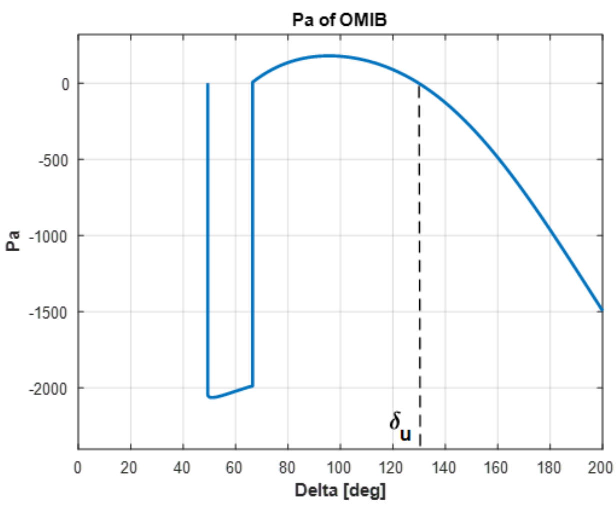

***Fig. 4**: OMIB P_a-δ trajectory for the unstable case.*

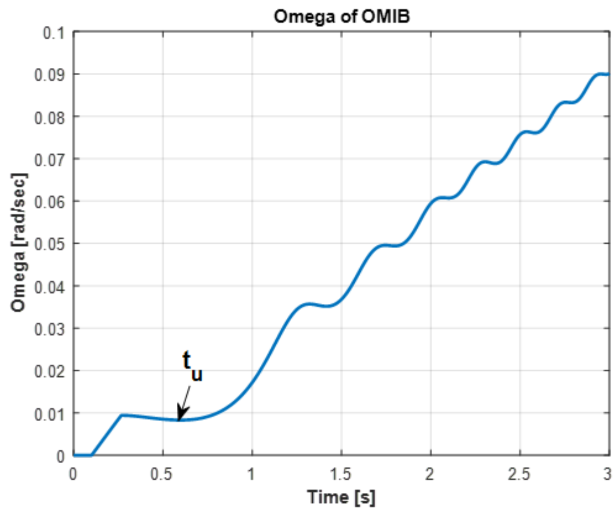

***Fig. 5**: OMIB ω trajectory for the unstable case.*

angle δ_u at time t_u and $P_a = 0$, as shown in Fig. 4. The time instant t_u can also be identified from the OMIB omega trajectory as shown in Fig. 5.

$$\omega(t_u) > 0 \qquad P_a(t_u) = 0 \qquad \eta_{st} = -\frac{1}{2}M\omega_u^2 \tag{13}$$

3. PROPOSED STABILITY MARGIN

The proposed method assumes that the synchrophasors (PMUs) are placed at all generator buses and the corresponding measurements are available online [14]. Using the OMIB P_a-δ trajectory of the SIME, a normalized transient stability margin (TSM) is proposed as:

$$A_{acc} = \int_{\delta_0}^{\delta_e} P_a d\delta \tag{14}$$

$$A_{dec} = \int_{\delta_e}^{\delta_u} P_a d\delta \tag{15}$$

where δ_0 is the starting instant of fault, δ_e is the instance of fault clearing, and δ_u is the final instance of observation.

The normalized transient stability margin (TSM), using the OMIB accelerating power is defined as:

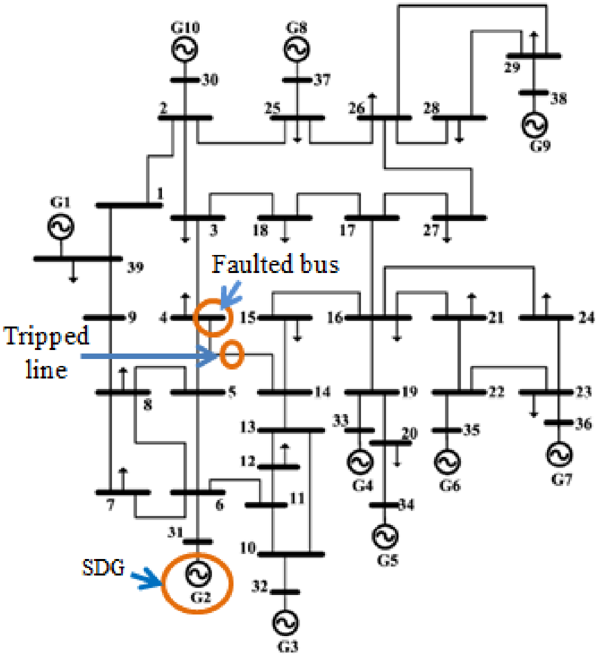

Fig. 6: *New England 39 bus test system.*

$$\eta = \begin{cases} \dfrac{A_{dec} - A_{acc}}{A_{dec}}, & \text{if } A_{dec} > A_{acc} \text{ (Stable)} \\[2ex] \dfrac{A_{dec} - A_{acc}}{A_{acc}}, & \text{if } A_{acc} > A_{dec} \text{ (Unstable)} \end{cases} \tag{16}$$

The stability margin defined above will have a positive value for stable cases from 0 to 1. The stability margin will have a negative value of −1 to 0 in the case of instability. Therefore, the normalized transient stability margin will be in the range of −1 to 1. The proposed stability margin is unique in that it provides a numerical estimate of the transient stability risk, which is helpful for the power system operator to take post-fault corrective action to maintain system stability.

4. REGRESSION MODELS

Regression analysis (RA) is used to mathematically describe the relationship between a set of independent variables and the dependent variable. Regression analysis can not only be used for assessing the strength of the relationship between variables but also for modeling the future relationship between them. There are multiple variations of regression analysis, such as linear, multiple linear, and non-linear. In statistics, simple linear and multiple linear RA are the commonly used models. Whereas for more complicated models, non-linear RA is used. In this paper, MATLAB is used for prediction of the stability margin. The Regression Learner App (RLA) [32], available in MATLAB, is used in this study. The RLA has a user-friendly environment where one can choose the desired model out of the many models available. In

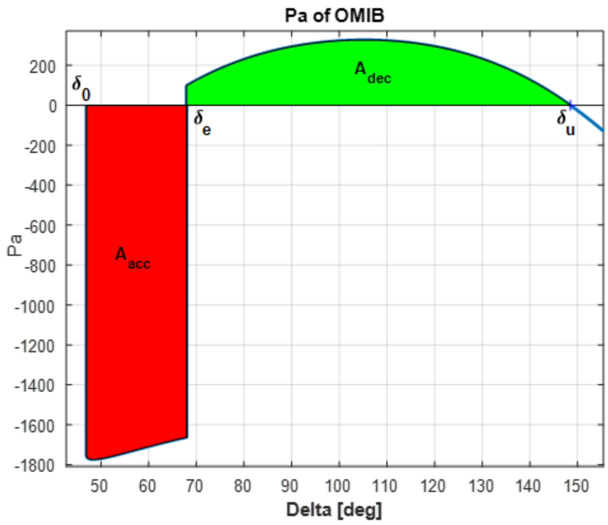

Fig. 7: *OMIB P_a-δ trajectory under the unstable condition.*

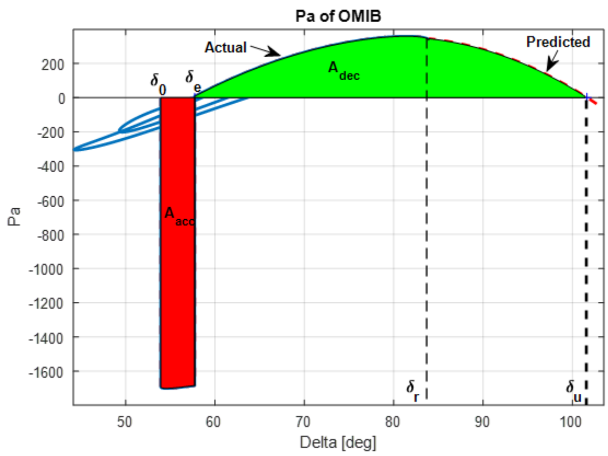

Fig. 8: *OMIB P_a-δ trajectory under the stable condition.*

the RLA, one can automatically train, validate different models, compare their performance, and choose the best one. The different models available in the RLA are linear regression (LR), decision trees (DT), support vector machines (SVM), an ensemble of trees, and Gaussian process regression (GPR).

5. SIMULATION AND RESULTS

The proposed approach applies the New England 39 bus test system consisting of 10 generators, 29 load buses, and 46 transmission lines as shown in Fig. 6. The power flow was performed using the MATPOWER simulation package [30]. The transient simulations were carried out in the MatDyn simulation package [31]. To demonstrate the proposed method, a three-phase fault was considered at bus 4. When the fault was cleared after 12 cycles by opening the line between buses 4 and 14, the post-fault system entered an unstable condition and the TSM obtained was −0.4697. The unstable case was clearly identified by the negative sign exhibited by the

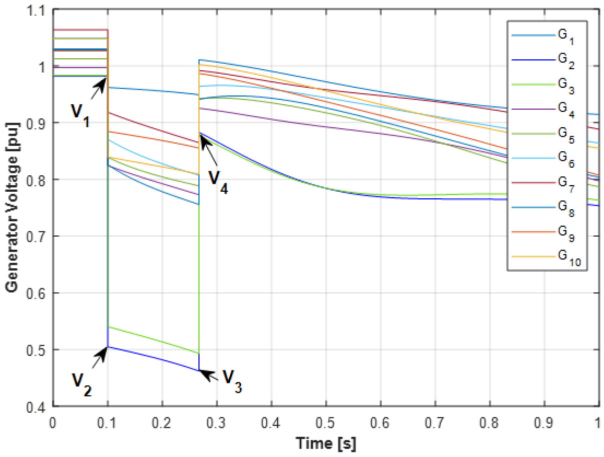

***Fig. 9**: Generator bus voltages for a fault at bus 4.*

TSM. The trajectory of accelerating power for this case is shown in Fig. 7. This fault was then cleared after five cycles by removing the same line, resulting in a stable case. The TSM value obtained was 0.37 with the OMIB P_a-δ trajectory, as shown in Fig. 8.

The measurements at four instants were given as inputs to the regression models to predict the following instances: (i) immediately prior to the fault; (ii) when the fault starts; (iii) fault clearing; and (iv) immediately after fault clearing. The OMIB rotor angle at instants (i) and (iv), the OMIB accelerating power (P_a) at instants (ii), (iii), and (iv). The voltages of the severely disturbed generator bus at all four instants were given as inputs to the regression models. Thus, there were nine inputs in total, with the proposed transient stability margin being one output of the regression models. The generator bus exhibited the highest difference before and during the fault voltage magnitudes and was therefore chosen as the severely disturbed generator (SDG). Since the stability margin was derived from the OMIB P_a-δ trajectory, the inputs of the OMIB rotor angles and accelerating power were found to be directly related to the stability margin. The voltage magnitude of the SDG was chosen as the input because it reflects or provides information about the severity and location of the fault. The generator bus voltage magnitudes for the unstable case (fault at bus 4) are shown in Fig. 9. The voltage measurements of generator 2 (SDG) at four instants are marked as V_1, V_2, V_3, and V_4.

To generate the training database, a three-phase fault at a bus was used. The fault was cleared by opening the connected line. The operating condition of the load was varied from 80% to 120% of the base case with an increment of 10%. For each varied load condition, the generation was adjusted to give a valid load flow pattern. The fault duration was varied from 5 to 10 cycles. This resulted in a total of 2445 samples, 780 of which were unstable and the remaining 1665 cases stable.

The Regression Learner App (RLA) in MATLAB was used to predict the stability margin. The RLA can be used to automatically train the many popular regression models. Users can automatically compare the performance of each trained model and choose the best one. For this current study, different parameters were used as inputs to the regression models, with the best results obtained when using the nine inputs discussed earlier. The training performance of the various regression models in terms of root-mean-square error (RMSE) is given in Table 1. The highest RMSE of 0.2834 was obtained for the Robust Linear model and the lowest RMSE of 0.0635

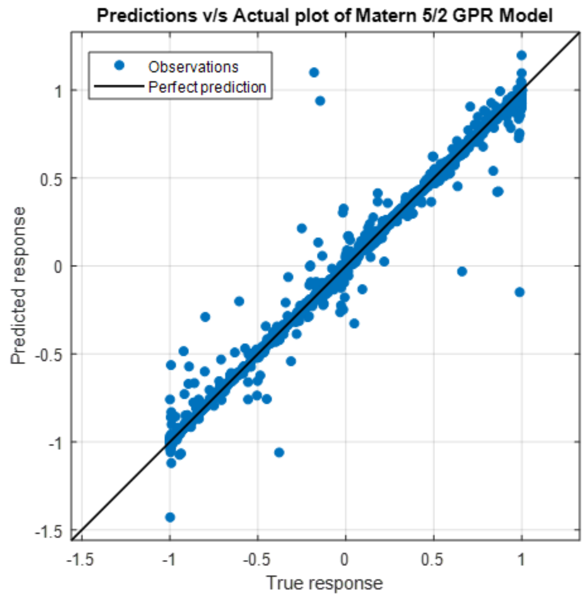

***Fig. 10**: Predicted versus actual plot of the Matern 5/2 GPR model.*

***Table 1**: Comparative performance of different trained models.*

Regression Model	RMSE
Linear	0.2595
Interactive Linear	0.2016
Robust Linear	0.2834
Stepwise Linear	0.2142
Fine Tree	0.1260
Medium Tree	0.1495
Coarse Tree	0.1888
Linear SVM	0.2678
Quadratic SVM	0.2265
Cubic SVM	0.1348
Fine Gaussian SVM	0.1253
Medium Gaussian SVM	0.1269
Coarse Gaussian SVM	0.2629
Ensemble of Boosted Trees	0.1602
Ensemble of Bagged Trees	0.1497
Squared Exponential GPR	0.0701
Matern 5/2 GPR	0.0635
Exponential GPR	0.0737
Rational Quadratic GPR	0.0654

***Table 2**: TSM prediction results using different GPR models.*

Faulted Bus	Removed Line	Clearing Time (cycles)	TSMI (η) Actual	Squared Exponential	Matern 5/2	Exponential	Rational Quadratic	Assessment
2	2-3	10	−0.1147	−0.1143	−0.1150	−0.1145	−0.1135	Unstable
2	2-25	10	−0.1604	−0.1566	−0.1584	−0.1605	−0.1604	Unstable
3	3-18	10	−0.1695	−0.1673	−0.1681	−0.1691	−0.1678	Unstable
4	4-5	8	0.2082	0.2116	0.2098	0.2082	0.2080	Stable
6	6-11	5	0.4009	0.3970	0.3983	0.4010	0.3996	Stable
6	6-17	7	−0.228	−0.2281	−0.2307	−0.2277	−0.2279	Unstable
8	8-9	6	0.4314	0.4345	0.4337	0.4314	0.4320	Stable
10	10-13	9	0.2395	0.2361	0.2369	0.2392	0.2389	Stable
13	13-14	7	0.3536	0.3519	0.3540	0.3537	0.3542	Stable
16	16-21	8	−0.6386	−0.6426	−0.6427	−0.6388	−0.6369	Unstable

***Table 3**: Training results of the Matern 5/2 GPR model.*

Parameter	Value
RMSE	0.063513
R^2	0.99
MSE	0.0040339
MAE	0.017113
Prediction speed (obs/s)	7300
Training time (s)	663.47

***Table 4**: Results obtained by the Matern 5/2 GPR model.*

Faulted Bus	Removed Line	Clearing Time (cycles)	TSMI (η) Actual	Predicted	% Error	Assessment
2	2-3	10	−0.1147	−0.115	−0.26	Unstable
2	2-25	10	−0.1604	−0.1584	1.24	Unstable
3	3-18	10	−0.1695	−0.168	0.91	Unstable
4	4-5	8	0.2082	0.2098	−0.77	Stable
6	6-11	5	0.4009	0.3983	0.65	Stable
6	6-17	7	−0.228	−0.2306	−1.13	Unstable
8	8-9	6	0.4314	0.4337	−0.53	Stable
10	10-13	9	0.2395	0.2369	1.09	Stable
13	13-14	7	0.3536	0.3539	−0.08	Stable
16	16-21	8	−0.6386	−0.6427	−0.64	Unstable

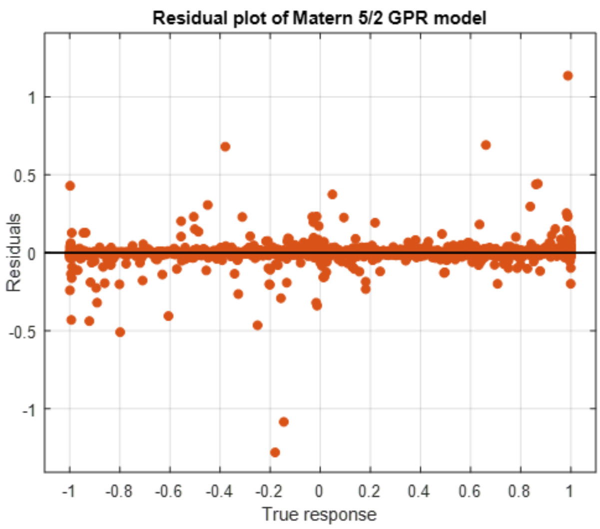

***Fig. 11**: Residual plot of the Matern 5/2 GPR model.*

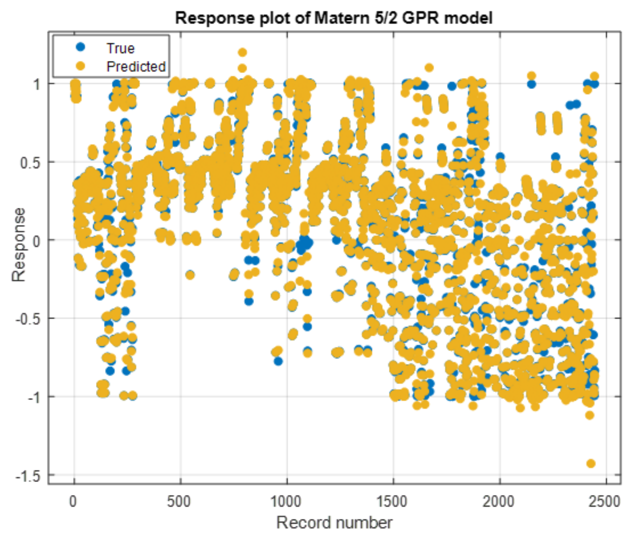

***Fig. 12**: Response plot of the Matern 5/2 GPR model.*

for the Matern 5/2 Gaussian Process Regression (GPR) model. Compared to other models, the performances of the GPR models were found to be very good. Default parameters were used for training all the models. The TSM predictions by different GPR models are presented in Table 2.

The predicted versus the actual plot, residual plot and response plot of the Matern 5/2 GPR model are shown in Figs. 10, 11, and 12. The results of the Matern 5/2 GPR model training are given in Table 3, along with the transient stability margin prediction results obtained by the Matern 5/2 GPR model in Table 4. The first six rows of the Table 4 relate to the trained cases. It can be observed that the Matern 5/2 GPR model is able to predict the results with very good accuracy. From a comparison of the results, it is clear that the synchrophasor measurements of the Matern 5/2 GPR model can be used for online prediction of transient stability.

6. CONCLUSION

In this paper, a synchrophasor-based online transient stability assessment method is proposed with a novel transient stability margin. Using the synchronized measurements, different regression models are trained to predict the post-fault transient stability margin. The performance between different machine learning regression models is compared in terms of RMSE for predicting the proposed transient stability margin. Among all the models, the Matern 5/2 GPR machine learning model produced the best performance.

The proposed method is fast and can be used for online transient stability assessment. Furthermore, it can be used for any multimachine power system and is independent of the machine model. By applying this method and classifying the contingency into stable or unstable, the operator can obtain information on the severity of the contingency in terms of the stability margin. It can be observed from the results that the proposed method is reliable and accurate in the prediction of transient stability and suitable for the online environment.

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