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Synchronized Measurements based Online Transient Stability Assessment using Gaussian Process Regression

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Abstract

In this paper an online post-fault Transient Stability Assessment (TSA) method using synchronized measurements or PMU measurements and Gaussian Process Regression (GPR) is presented. A post-fault multi-machine system is converted into two machine groups (Critical and Non critical) then into a suitable OMIB system using Single Machine Equivalent (SIME) method. With the help of thus obtained OMIB Pa-δ trajectory, a normalized Transient Stability Margin (TSM) is proposed offline. By using pre and during fault synchronized measurements as input, different GPR models are trained offline to predict the normalized stability margin. Keeping RMSE as a measure, a best suitable model is chosen for prediction. After a fault, the synchronized measurements are used as input to this trained model to predict the stability margin online. If the predicted margin is negative, then the post-fault system said to be unstable. If the predicted margin is positive, then the system is stable. The proposed assessment method is tested using New England 39 bus test system. The results are compared with offline simulations. High prediction accuracy rates are observed for GPR models, making them suitable for online TSA.

Keywords: Gaussian Process Regression (GPR), Regression Analysis, Single Machine Equivalent (SIME), Synchronized Measurements, Transient Stability Prediction, Transient Stability Margin (TSM)

1. Introduction

Online transient stability assessment after the occurrence of a large disturbance such as fault, sudden loss of large load or a large generator etc. is very important. Even though the occurrence of transient instability is rare but if occurred, its detection and mitigation by using suitable control action is very important. In this regard online assessment of transient stability plays an important role in today's large interconnected power systems. Transient stability of a power system is related with the ability of that system to remain in synchronism after subjected to a large disturbance as stated above[1–3]. The occurrence of transient instability may lead to cascaded failures or even may lead to block-outs. In order to avoid these kinds of problems it is necessary to maintain and operate with sufficient stability margins. This is possible only when the operator has clear information about operating stability margin. In this paper a synchronized measurements based online scheme for prediction of normalized transient stability margin using GPR models is proposed.

Time Domain Simulation (TDS) method is the practical accurate method used for TSA of the large power systems with detail modeling of its components. Because of high dimensionality and nonlinearity large computation time is required for TDS which makes it difficult to use it for online stability assessment. Transient Energy Function (TEF) methods also known as direct methods[4–6] overcome this heavy computation burden of TDS method, but these methods also suffer from limited scalability and conservativeness which make them less suitable for online applications. Hybrid methods which are obtained by combining both TDS and TEF methods[7–12] improve the performance of TEF methods. Another category of TSA methods are machine learning or artificial intelligence approaches such as Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM), fuzzy based systems, Extreme Learning

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Machines (ELM) etc. With good database and training these methods can assess the stability of the system with good accuracy. The high speed accurate prediction makes them more suitable for online applications.

With the availability of synchronized measurements these machine learning methods are becoming more useful in online applications. These methods are faster and more accurate compared to other methods. In[13] PMU measurements based model-free method for post-fault transient instability prediction is proposed using ensemble online sequential learning machine. Initially a multi-machine system is converted into OMIB system and then using OMIB-ω trajectory transient stability is assessed. The synchronized measurements are collected locally with phasor data concentrators and then transmitted to a central decision maker. Such architecture, along with fast communication arrangement, has the potential of realizing accurate and efficient real-time DSA[14]. In the work presented in[15], the PMU measurements from generator buses are used for estimation of post-fault transient stability margin by TEF technique. In literature[16], a two-stage method for online identification of power system dynamic signature using PMU measurements and data mining is proposed. Using an initially constructed binary training database for all contingencies rotor angles are predicted using DT. If the system is found unstable then using predictors a multiclass classifier identifies the dynamic behavior of the unstable case.

A data mining approach using ensemble decision trees with PMU data, an online dynamic security assessment scheme is described in[17]. Using random subspace method multiple small decision trees are initially trained offline. Then in near real time, the performance of these small decision trees is re-checked with new cases. If any PMU data is missing in online DSA then feasible small decision trees are identified and a boosting algorithm is engaged to compute the voting weights of feasible small decision trees. The conclusion of security classification for online DSA is found through a weighted voting of feasible small decision trees. A novel online transient stability prediction system based on only 10-12 sample fault data collected by geographically distributed PMUs without resolving computationally widespread electromechanical dynamics is presented in[18]. Thus collected PMU data is synchronized and analyzed on a computing platform to predict the generator trajectories to assess the stability of the system.

In literature[19], a regression tree approach for prediction of the power system stability margin and to detect the forthcoming system event is presented. Synchronized voltage and current phasors are used as input features for the Regression Tree (RT) to predict voltage and oscillatory stability margins. A PMU and DT based online dynamic security assessment system for large interconnected power system[20]. Here the DTs are periodically updated offline to provide security assessment and corrective guidelines online based on real time measurements. Taking PMU sampled bus voltage phasor, a convolution neural network based transient stability assessment and instability mode prediction process[21]. The prediction was carried out by observing a short window after the disturbance. In[22] a unified approach for prediction of both small-signal and rotor angle stability using an online deep learning technique is proposed. The employed deep learning techniques use the voltage phasor measurements which are collected across the system for training the online prediction model for stability prediction.

The authors in literature[23] present an algorithm for online out-of-step prediction using generator acceleration power and rotor speed deviation by ellipse fitting. A unique measurement-simulation based hybrid method for transient stability assessment and emergency control scheme is discussed in[24]. Using the deviation between an offline simulation trajectory and online trajectory of an equivalent single machine infinite bus system, a deviation energy index is defined for fast online transient stability assessment. A new early stage detection of unstable conditions in large power systems by introducing a reduced order dynamic model for each control area formed by aggregation of generators and their associated controllers is proposed in0[25]. From the available online measurements, a sensitivity analysis is used to improve the performance and efficiency of the proposed estimator. A real-time stability index is proposed for stability assessment.

In the proposed approach SIME method is used to transform a multi machine system into its equivalent OMIB system. Then using the accelerating and decelerating area of the equivalent OMIB Pa-δ trajectory, a normalized transient stability margin is defined. The defined stability margin not only gives the stability status of the post fault system but also gives the information about severity of the contingency. Offline time domain simulations are carried out to build the required database considering different operating conditions and contingencies. Using the database GPR regression models are trained offline to predict the TSM online. The simulations are carried out using Matlab based simulation packages[26–28].

2. Single Machine Equivalent (SIME) Method

SIME method[7] is a hybrid method. It is a combination of TDS and equal area criterion concept. It is a model free approach using which any complex system components can be modeled with different order models. This method can also be used to access the system in terms of CCT, stability margin and contingency ranking. In SIME method by observing post-fault rotor angles of generators obtained by TDS, the multi-machine system is reduced into equivalent two machine groups. Then these two groups are reduced into equivalent OMIB. Critical Machines (CM) are the one which swing together and are likely to lead the post-fault power system into unstable condition. Non-critical machines (NM) are the one which swing together and remain in stable condition even after the power system becomes unstable. Center of Angle Reference (COA) frame is used to construct the OMIB for SIME.

The expressions for OMIB parameters are given below.

The rotor angles and speed for critical machines, C:

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

$$\omega_C(t) = \frac{1}{M_C} \sum_{k \in C} M_k \, \omega_k(t) \tag{2}$$

For non-critical machines, N:

$$\delta_N(t) = \frac{1}{M_N} \sum_{j \in N} M_j \, \delta_j(t) \tag{3}$$

$$\omega_N(t) = \frac{1}{M_N} \sum_{j \in N} M_j \, \omega_j(t) \tag{4}$$

The equivalent OMIB parameters:

Rotor angle:

$$\delta_{OMIB} = \delta_C(t) - \delta_N(t) \tag{5}$$

Rotor speed:

$$\omega_{OMIB} = \omega_C(t) - \omega_N(t) \tag{6}$$

Mechanical power:

$$P_m(t) = M\left(\frac{1}{M_C} \sum_{k \in C} P_{mk}(t) - \frac{1}{M_N} \sum_{j \in N} P_{mj}(t)\right) \tag{7}$$

Electrical power:

$$P_e(t) = M\left(\frac{1}{M_C} \sum_{k \in C} P_{ek}(t) - \frac{1}{M_N} \sum_{j \in N} P_{ej}(t)\right) \tag{8}$$

Accelerating power:

$$P_a(t) = P_m(t) - P_e(t) \tag{9}$$

$$M_C = \sum_{k \in C} M_k; \qquad M_N = \sum_{j \in N} M_j;$$

$$M = \frac{M_C M_N}{M_C + M_N}$$

3. Normalized Transient Stability Margin

In the proposed method the assumption is made that PMUs are placed on all the generator buses and their synchronized measurements are available online[14]. Using the OMIB Pa-δ trajectory of SIME, a normalized TSM is proposed as given below.

$$\mathbf{A_{acc}} = \int_{\delta_0}^{\delta_e} \mathbf{P_a} \, \mathbf{d\delta} \tag{10}$$

$$\mathbf{A_{dec}} = \int_{\delta_e}^{\delta_u} \mathbf{P_a} \, \mathbf{d\delta} \tag{11}$$

where, δ_0 – fault starting instant

δ_e – fault clearing instant

δ_u – end of observation

Normalized accelerating power based transient stability margin (TSM),

$$\eta = \begin{cases} \dfrac{\mathbf{A_{dec} - A_{acc}}}{\mathbf{A_{dec}}} & \textbf{If } \mathbf{A_{dec} > A_{acc}} \ (\textbf{Stable}) \\ \dfrac{\mathbf{A_{dec} - A_{acc}}}{\mathbf{A_{acc}}} & \textbf{If } \mathbf{A_{acc}} > A_{\mathbf{dec}} \ (\textbf{Unstable}) \end{cases} \tag{12}$$

The above defined normalized stability margin is positive and lies between 0 to 1 for stable cases where decelerating area is more than the accelerating area. It is negative and lies between -1 to 0 for unstable cases. Thus the stability margin lies between -1 to 1.

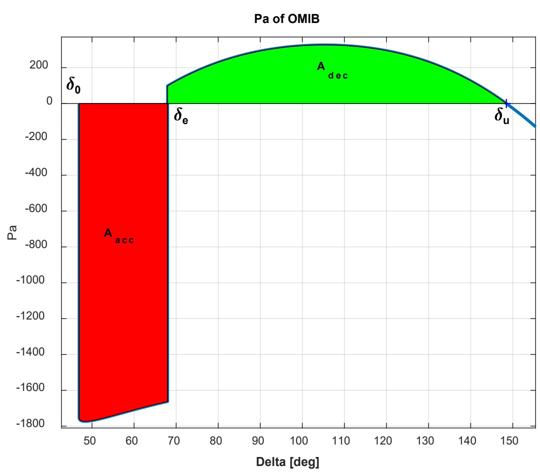

Figure 1. OMIB P_a-δ trajectory for an unstable case.

4. Gaussian Process Regression Models

In mathematics, Regression Analysis (RA) is used to define the relation between a set of independent variables and a dependent variable. Regression analysis can be used for assessing the strength of the relationship between variables and also for modeling the future relationship between them. There are multiple variations of the 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. The RLA has a user-friendly environment where one can use desired model out of many models available. In RLA one can automatically train, validate different models and compare their performance and choose the best one. Different models available in RLA are linear regression (LR), decision trees (DT), support vector machines (SVM), gaussian process regression (GPR) and ensemble of trees. In this paper for prediction of normalized TSM, performance of various GPR models available in Regression Learner App (RLA)[28] of matlab are studied. RMSE is used as performance indicator for comparison of different GPR models.

5. Simulations and Results

The proposed approach is applied to New England 39 bus system shown in Figure 2. The test system has 10 generators, 29 load buses and 46 transmission lines. The load flow analysis simulations were carried out using MATPOWER[26]. The dynamic simulations were performed using MatDyn[27]. The database was generated by considering different load scenarios varying from 80 to 120% of base case with an increment of 5%. A three phase fault at a bus was considered and was cleared by opening of the connected line. The fault duration of 5 to 10 cycles was considered. Totally 2446 valid cases including 901 unstable and 1545 stable cases were obtained.

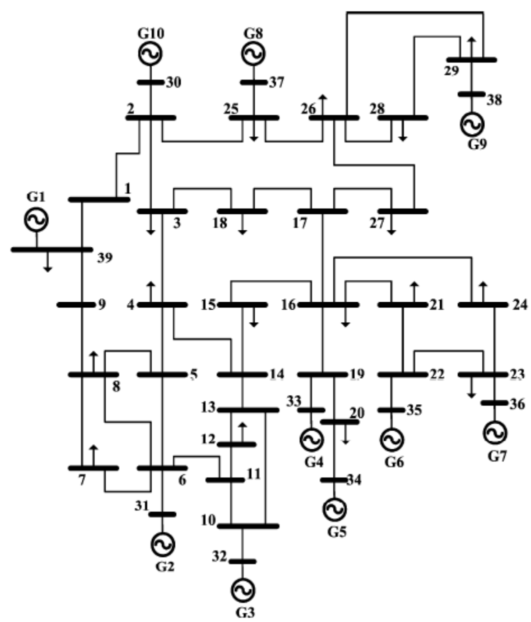

Figure 2. New England 39 Bus Test System.

GPR models of Regression Learner App in matlab were used for prediction of stability margin. The generator connected to the bus with highest difference between pre and during fault voltage is termed as severely disturbed generator (SDG). The bus voltage magnitudes at four different instances and rotor angles at two instances of this SDG are chosen as inputs to the GPR models. The instances considered for synchronized measurements are (i) just before fault starting (ii) fault starting (iii) fault clearing (iv) immediately after fault clearing. The bus voltage magnitudes at all four instances as indicated in Figure 3 and rotor angles at instants (i) and (iii) are chosen as inputs. Normalized TSM is the output of the GPR models.

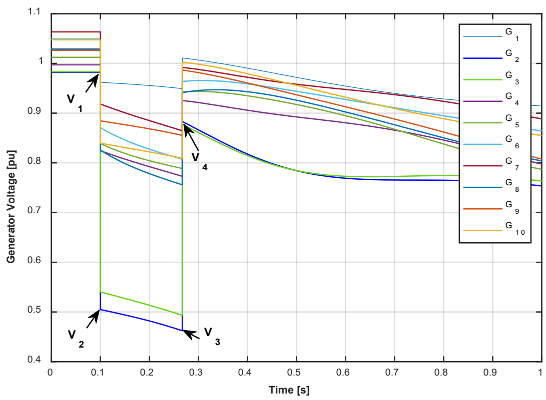

Figure 3. SDG bus voltage measurements.

Four different GPR models with RMSE as the training performance indicator were investigated for TSM prediction. The RMSE values of all the four GPR models are listed in Table 1. Comparing the RMSE values of all the models, Exponential GPR model has least RMSE value. The prediction values of TSM obtained by four GPR models for different fault locations and fault clearing times are given in Table 2. The actual values of normalized TSM computed as per equation 12 are also given for comparison. From the predicted values of TSM the contingencies can be classified as stable or unstable accurately. It can also be observed from the results that the prediction and classification accuracy is good in case of Exponential GPR model.

Table 1. Performance of GPR models

Regression Model	RMSE
Squared Exponential GPR	0.14067
Matern 5/2 GPR	0.10594
Exponential GPR	0.08711
Rational Quadratic GPR	0.09073

Table 2. Comparison of prediction results by different GPR models

Faulted Bus	Removed Line	Clearing Time (cycles)	TSMI (η)					Assessment
			Actual	Squared Exponential	Matern 5/2	Exponential	Rational Quadratic	
4	4-14	10	-0.7768	0.0110	-0.0631	-0.7679	-0.0634	Unstable
21	21-22	7	-0.7058	-0.7048	-0.7051	-0.7057	-0.7057	Unstable
26	26-29	10	-0.9365	-0.9330	-0.9349	-0.9365	-0.9364	Unstable
3	3-18	9	-0.6365	-0.6337	-0.6344	-0.6364	-0.6360	Unstable
1	1-2	5	0.8579	0.8631	0.8648	0.8579	0.8581	Stable
5	5-8	6	0.1480	0.1501	0.1501	0.1481	0.1486	Stable
9	9-39	8	0.4659	0.4597	0.4649	0.4659	0.4660	Stable
7	7-8	6	0.2877	0.2895	0.2896	0.2878	0.2877	Stable

6. Conclusion

In this paper a synchronized measurement based online transient stability assessment method using four different GPR models is presented. The results are compared with the actual TSM values obtained by TDS-SIME trajectories. Best results are obtained with Exponential GPR model. With the availability of synchronized measurements, the proposed method can be used for online prediction of TSM.

The method provides fast, reliable and accurate results in case of online TSA. The method can be used for any multi-machine power system and is independent of the machine model used. Using this method along with classification of a contingency into stable or unstable, the operator gets the information about severity of the contingency in terms of stability margin.

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