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A Deep Learning-Based Approach for Comprehensive Rotor Angle Stability Assessment

*M. Shahriyari, H. Khoshkhoo**
Faculty of Electrical Engineering, Sahand New Town, Tabriz, Iran.

Abstract- *Unlike other rotor angle stability assessment methods which only deal with either transient or small-signal (SS) stability, in this paper, a new stability prediction approach has been proposed which considers both transient and SS stability status. Therefore, the proposed method, which utilizes Multi-Layer Perceptron-based deep learning model, can comprehensively predict the post-disturbance rotor angle stability. Since the proposed method uses the voltage of the generating units directly measured by WAMS in the early moments after the disturbance occurrence and does not need to calculate the generators' rotor angle (which requires a high computational burden), it can timely predict the stability stiffness using data provided by PMUs installed at generators' buses. In this respect, this method provides a proper chance for the system operators to take appropriate corrective measures. To evaluate the proposed method's efficiency, it has been implemented and tested on IEEE14-bus and IEEE 39-bus test systems. The dynamic simulation results show that although the proposed method requires fewer PMUs than previous methods that exist in the literature, it can timely evaluate the stability status. Also, to properly show the power system stability stiffness from the transient and SS stability point of view, the suggested method accurately classifies the post-disturbance operating point into Unstable, Alarm, or Normal categories.*

Keyword: Transient stability, small-signal stability, rotor angle stability, deep learning, dynamic stability assessment.

1. INTRODUCTION

The rotor angle stability indicates the ability of synchronous generators (SGs) to remain synchronism when a contingency occurs in a power system. According to the size of a disturbance, this type of instability can be divided into two categories, including large-signal (transient) and SS stability, which are vital subsets of the network stability and have a significant influence on the planning and operation of these systems.

When a disturbance causes the operating point to pass the stability boundaries, if desired remedial actions are not taken at the right time, the rotor angle of some generators will increase/decrease continuously or show undamped oscillatory behavior which causes the separation of the generators' rotor angles and may lead to cascading outages and blackouts [1]. Besides, in the post-disturbance condition, even if the synchronism is maintained and the system moves towards a stable equilibrium point, in a short time, the low damping ratio of the system may push the operating point towards the instability boundary and cause SS instability. Therefore, in order to perform an efficient corrective action, it is essential to predict both the transient and SS stability status rapidly and perform the required remedial actions.

The power networks' dynamic response is described using Differential-Algebraic Equations (DAE) which consider the dynamic behavior of power systems equipment (FACTs, Loads, SGs control systems, etc.) [2]. In order to analyze the post-disturbance operating point from SS stability point of view, the linearized DAE can be used to determine the dominant eigenvalues which significantly affect the dynamic behavior of the network [3].

The transient stability assessment procedures can be classified into model-free and model-based methods. Among model-based methods, the time domain simulation-based approaches are the most accurate ones [4]. However, these methods are time-consuming and have a high computational burden. In addition, although energy function-based methods can quickly evaluate the transient stability, they omit the higher order of synchronous generator models and also, neglect their controllers [5]. Equal Area Criterion method and

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*Corresponding author:
E-mail: khoshkhoo@sut.ac.ir (H. Khoshkhoo)
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sensitivity analysis technique [6] are other model-based methods that are used widely in literature and due to the nonlinear behavior of the system equipment, they cannot predict the stability status. On the other hand, model-free methods do not require the network model in the online application and usually use artificial intelligence tools and curve-fitting approaches [6]. During the last decade, due to the existence of the wide-area measurement system (WAMS), which makes the dynamic behavior of power systems visible, artificial intelligence-based methods have been widely used for high-speed assessment of the power system stability status in online applications [7]. The model-free based methods that predict transient stability mainly include decision tree (DT) [8], Long Short-Term Memory (LSTM), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM) [9-10]. These tools are trained using data obtained from offline simulations and then, used for fast assessment of the stability status in the online applications.

During the last years, deep learning tools which utilize the neural network architecture have been used to evaluate the stability status [11-13]. However, these methods only analyze the transient stability status and do not consider the SS stability of the post-disturbance operating point. In other words, although (in those networks whose dominant eigenvalues are close to the imaginary axis) any changes in the system loading and/or topology may result in instability, these research works neglect it and only assess the transient stability status. For instance, in Ref. [10], the autoencoder algorithm is used to select the proper feature set and then, the selected features (including the rotor angle of generators) are used to train a CNN-based classifier to assess the stability status. However, there are two separate training sections for CNN and autoencoder [12]. Also, such a feature set cannot be achieved directly from PMU measurements and requires time-consuming calculation. In Ref. [9], two LSTM networks are utilized distinctly for transient stability status prediction by post fault information, including voltage phasor and the rate of change of frequency (ROCOF) measurements.

Meanwhile, a few research works have been proposed to detect SS stability using machine learning algorithms. For example, references [13] and [14] have tried to detect the damping ratio of system modes. However, these methods do not predict the final stability status and only receive data measured by WAMS and detect dominant eigenvalues in the next time-step (i.e., the near future). Also, although the method proposed in Ref. [15] predicts (i.e., far future) the transient stability status, it detects (i.e., near future) the small-signal stability (it cannot predict the small-signal stability). To overcome the problem mentioned above, in this paper, an integrated online method has been proposed to simultaneously predict the SS and transient stability status of the post-disturbance operating point. Table 1 compares the performance of the proposed method with some other methods that exist in the literature. As shown, while the proposed method considers different types of disturbances at all transmission lines, it (unlike other methods) quickly predicts both SS and transient stability and accurately classify the post-disturbance operating point into Unstable, Alarm, or Normal categories.

In this respect, the contribution of the proposed approach can be listed as follows:

- In this paper, an integrated method has been proposed for SS and transient stability status prediction utilizing online data received from PMUs. Therefore, the main contribution of this paper lies in the comprehensive rotor angle stability prediction and providing valuable information for the system operator to perform timely and optimal corrective actions.
- Unlike most of the previous approaches proposed in the literature, in this paper, the proposed feature set is directly calculated using data measured by WAMS and does not need to calculate the generators' rotor angle (which requires a high computational burden [15]).

Table 1. Comparison of the proposed method with some approaches proposed in the literature

Ref.	Test system	Required time	Contingencies		Transient	Small signal
[10]	127 bus	0.083 s	LLL	all lines	✓	-
[16]	118 bus 145 bus	0.123 s	LLL	all lines	✓	-
[17]	39 bus 140 bus	0.150 s	LLL	all lines	✓	-
[18]	2100 bus	N/A	LLL	Some lines	✓	-
[19]	39 bus	0.053 s	LLL	all lines	✓	-
[3]	39 bus	0.60 s	LLL	Some lines	✓	-
[15]	39 bus 68 bus 145 bus	0.210 s	LLL	all lines	✓	✓ (detection)
Proposed method	14 bus 39 bus	0.033 s	LLL LL LLG LG	all lines	✓	✓ (prediction)

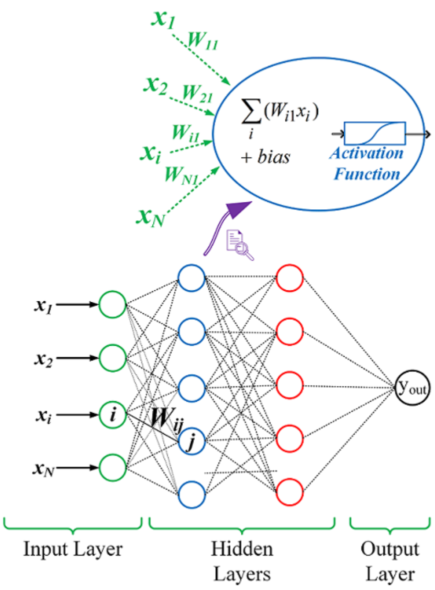

Fig. 1. The ANN-based MPL schematic

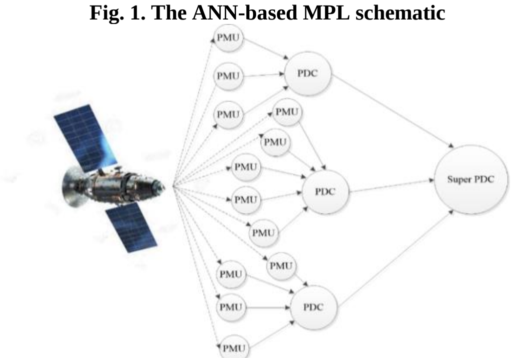

Fig. 2. The Hierarchical structure of WAMS

- The proposed feature set only requires data measured by those PMUs installed at generators' buses. In this respect, compared to other methods, this method requires fewer PMUs.
- A Multi-Layer Perceptron (MLP)-based deep learning model is used for SS and transient stability status prediction. In this respect, unlike other stability status prediction algorithms that only determine the stability or instability of the post-disturbance operating point, the proposed method is designed to assess the post-disturbance stiffness using multiple output labels that indicate Normal, Alarm, and Unstable conditions.

2. REQUIRED TOOLS

2.1. Multi-Layer Perceptron (MLP)

A multilayer perceptron (MLP) is a kind of fully connected artificial neural network which includes input, output, and some hidden layers which perform a non-linear transformation on the input feature set. In deep learning-based MLP, which is a proper tool for supervised classification and regression problems in nonlinear and complex systems, the hidden layers receive the weighted input data and use a bias and a nonlinear activation function (such as rectifier linear unit (ReLU), tanh, sigmoid, etc.) to generate and send the output to the next layer (Fig. 1) [20].

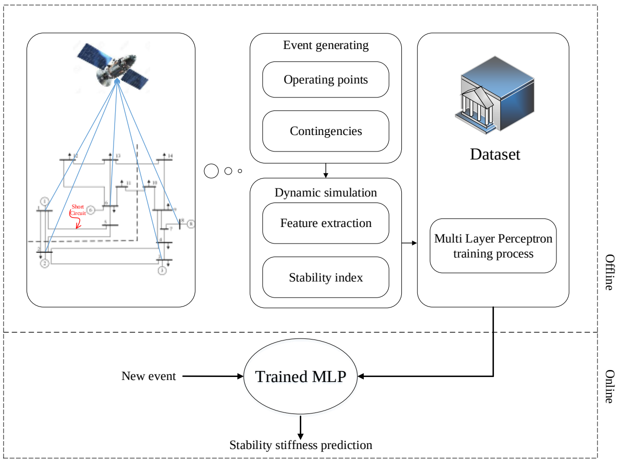

Fig. 3. The proposed MLP framework in the offline training process and online application

Finally, in the output layer, the dot product of the last hidden layer output, a bias, and an activation function is used to calculate the output variable(s). Obviously, the choice of the number of output neurons and the activation function depends on the type of classification/regression problem. In this respect, for the prediction of the network stability which may be labeled by 0 (Normal) or 1 (Alarm) or 2 (Unstable), a single output neuron and softmax activation function that output a value between zero and 2 seem to be proper selections. Due to the capability of MLP in the classification of nonlinear models, it seems to be a proper tool for forecasting the rotor angle stability of power grids which are complex and highly nonlinear networks. For this purpose, in the training phase, the back-propagation approach, which is a generalization of the least mean squares approach, is used to determine the appropriate bias and weights of the MLP classifier. Then, in online application, the trained MLP can be used for fast rotor angle (transient and SS) stability prediction [21].

2.2. Wide-area measurement system

The need for advanced systems in monitoring, improving the stability and security, and increasing the reliability of the network, has become a necessity because of the extensive size of the power networks [22]. In traditional systems, power system operators use SCADA to measure electrical variables of the system. However, due to the lack of the ability to measure time-synchronous values, this measurement system is not suitable for online monitoring of the dynamic behavior of networks. In this regard, during the last decade, WAMS are utilized worldwide to improve the monitoring of these networks [23]. According to the Fig. 2, WAMS is a hierarchical system and PMUs are at the end of this network. The measured parameters are sent from PMUs to Phasor Data Concentrators (PDCs) which gather PMUs data and omit incorrect data. Eventually, Supper Data Concentrator located at the highest step receives data from PDCs, and a decision-making process can be performed at this step [24].

3. THE PROPOSED APPROACH FOR ONLINE PREDICTION OF TRANSIENT AND SMALL-SIGNAL STABILITY

In the proposed method, a fast and precise MLP based classifier is provided to assess the dynamic behavior of the network. In this regard, offline training process and online application of the classifier are depicted in Fig. 3 which will be described in the following subsections.

3.1. Generation of operating points and disturbances

To reliably evaluate the network's stability, all possible operating points and events should be considered. Hence, all operating points far from or near the stability boundary should be used in offline simulations to train the MLP classifier properly. For this purpose, using dynamic simulations, step changes in the system loading (from low loading to high loading condition) are used to obtain new operating points. In addition, various contingencies should be considered in the event generation process. Therefore, in order to train a reliable classifier, different kinds of short circuits event with various fault duration at different locations on all lines are applied to the above-mentioned operating points to produce a comprehensive dataset (Table 2). The total number of generated events can be calculated as follows

$$N_{studyCases} = N_{op} \times N_{line} \times N_{ftype} \times N_{fLoc} \times N_{fDuration} \quad (1)$$

where N_{OP}, N_{line} N_{fType}, N_{fLoc}, $N_{fDuration}$ indicates the number of operating points, transmission lines, fault types (i.e., LL, LLL, LG, and LLG), fault locations on each line (=3), and considered fault clearing period, respectively. It should be noted that in the offline time-domain simulations, it has been assumed that according to the Direct Under-reaching Transfer Trip (DUTT) scheme, the first zone of the distance relays trips faulted line based on fault duration mentioned in Table 2.

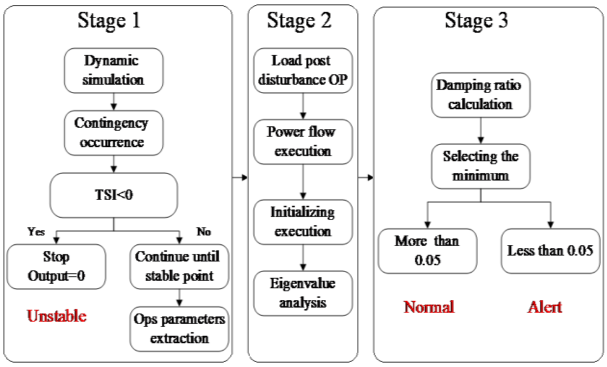

Fig. 4. The stability assessment procedure

Table 2. All possible contingencies considered in training the MLP classifier

Fault type	Fault location	Fault duration	Faulted lines
LLL LLG LL LG	1%, 50%, 99%	0.05-0.1 s (with the step of 0.01)	All lines

3.2. Dynamic simulations

Dynamic simulations are performed to assess the consequence of the aforementioned contingencies in multiple operating points. In this paper, to obtain the final status of the network, two indices that analyze the transient and SS stability status are used:

$$TSI = \frac{360 - |\Delta\delta_{max}|}{360 + |\Delta\delta_{max}|} \quad (2)$$

where $\Delta\delta_{max}$ is the maximum difference of rotor angles between any two generators [11]. Also, TSI<0 indicates that the system will become unstable from the transient stability point of view. On the other hand, the power system is stable in terms of SS stability when all eigenvalues have negative real parts. Therefore, in this paper, the minimum damping ratio is used as a SS stability index which is calculated by [25]:

$$SSSI = \frac{-\alpha}{\sqrt{\alpha^2 + \omega^2}} \quad (3)$$

where α is the real part and ω is the imaginary part of an eigenvalue. In this paper, since SSSI < 0.05 may threaten the network stability, it is assumed that in such operating points, the system is in Alert condition [26]. The procedure of analyzing the transient and SS stability using DIgSILENT PowerFactory software is shown in Fig. 4. According to this flowchart, TSI<0 indicates that the post-disturbance operating point is unstable and, if in the post-disturbance condition the system reaches a stable equilibrium point, eigenvalue analysis is used to classify the operating point to Alert and Normal as follows:

$$Rotor\ angle\ stability\ status = \begin{cases} Unstable & if \quad TSI < 0 \\ Emergency & if \quad SSSI < 0.05 \\ Normal & if \quad SSSI > 0.05 \end{cases} \quad (4)$$

It should be stated that in offline simulations, it has been supposed that the contingency occurs at t=1s and PMUs placed at generator buses measure the variables every 1/60 s [27].

3.3. Feature Selection and Model Training

3.3.1. Feature selection

Obtaining an efficient feature set that can predict both SS and transient stability status of the power system precisely is a challenging process. In the post-fault condition, stability status prediction of the network becomes easier as time passes.

Table 3. The proposed feature set

Symbol	Feature	Time of sampling
V_{G0}	Pre fault voltage magnitude of generators	Just before fault occurrence
V_{G1}	Voltage magnitude of generators in post fault trajectory	1.0167 s
V_{G2}	Voltage magnitude of generators in post fault trajectory	1.033 s
Line	Faulted line	------
F.T	Type of the short circuit	------
F.L	Fault Location on line	------
F.D	Fault Duration (fault clearance -fault occurrence)	------

Therefore, the later the PMUs measurements are made, the more accurate prediction can be achieved. However, early assessment of the post-disturbance stability status will provide more chances for power system operators to execute necessary control actions.

When a contingency occurs in a power system, fault-dependent and independent variables can affect systems behavior. Therefore, as can be seen in Table 3, in this paper both factors are considered in obtaining an appropriate feature set. In this paper, fault-dependent features contain fault duration, type and, location (on each line), and fault-independent ones include terminal voltage magnitude of synchronous generators. It should be stated that since the voltage of the generators quickly responds to the disturbance, these variables have been selected to predict the stability status in the initial moments after the fault occurrence.

3.3.2. Deep learning model and training process

A MLP classifier, fb, trained offline and constructed (according to Fig. 1) using the dataset, M = {(x1, y1), . . . , (xM, yM)}, to map, fb(xi)=yi, by minimizing lost function using an optimizer. It should be stated that in this dataset, xi and yi represents the parameters of the feature set and output mapping of xi, respectively. Also, in this paper, the performance of three different optimizers (i.e., Stochastic Gradient Decent (SGD) with learning rate equals to 0.01, Adam, and Adadelta) will be analyzed [14, 28].

In offline dynamic simulations, when a contingency occurs in the power system, both stability status (which are labeled as Unstable, Alert, and Normal) and feature set parameters (Table 3) are gathered to obtain a comprehensive dataset. Then, using python software, this dataset is utilized for model training based on the 10-fold cross-validation algorithm [29]. It is worth mentioning that although the training process is time-consuming, it is executed in the offline phase and will not affect the speed of the method in the online applications. According to Figure 5, the proposed classifier has four hidden layers, the last of which is the dropout layer. The dropout layer’s task is to eliminate additional computation burdens and prevent the model from becoming more complicated. In this paper, the dropout layer is located into MLP structure (at the end of hidden layers) to prevent over-fitting during the training process, with a rate of 0.2 [30]. The hidden layers contain 60, 40 and, 20 neurons, respectively, were obtained from extensive trial and error tests to get the best possible result.

4. SIMULATION RESULTS

The effectiveness of the suggested method is examined in IEEE 14-bus and IEEE 39-bus networks whose results will be described in the following subsections. It is worth mentioning that although the proposed method is fast, the transfer delay of PMUs' measurements will cause a delay in gathering the measurement, calculating the feature set, and predicting the stability status. However, since this delay is about several tens of ms (100 – 700 ms mentioned in [31]), it will lead to a short delay in post-disturbance stability assessment. Therefore, in these simulations, the transfer delay of PMUs measurements is neglected. It should be stated that all approaches that require synchrophasors for analyzing the stability status will have such a problem.

4.1. IEEE 14-bus test system

Based on the procedure described in Section 3, the offline time-domain simulations are carried out in IEEE 14-bus test system to analyze the impact of the 1152 short circuits (4 fault types, 6 fault duration, and 3 fault locations at 16 transmission lines) at two operating points. For instance, Fig. 6 and Fig. 7 show two examples of unstable and stable cases where LLL short circuit fault with fault duration of 0.05 s occurs at 50% of Line 1 and Line 7, respectively. Finally, according to the criteria mentioned in Eq. (4), the post-disturbance condition of these dynamic simulations have been classified into 180 unstable, 1209 Alert, and 915 Normal cases.

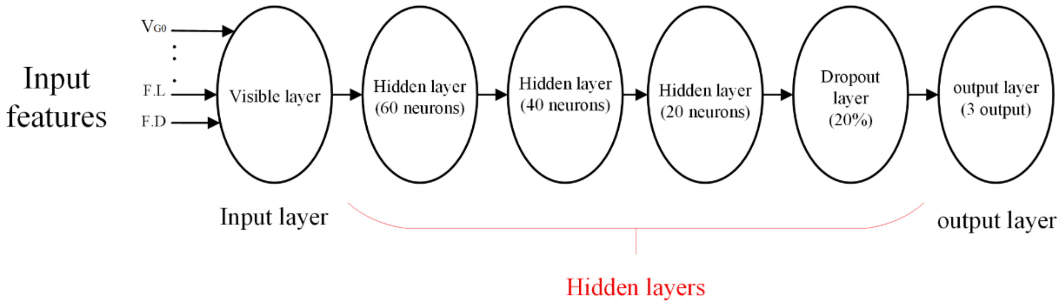

Fig. 5. The MLP structure.

Then, as mentioned earlier, the results of the offline dynamic simulations are used to calculate the feature set which is fed into MLP-based deep learning classifier (performed in python 3.6) as a dataset. Then, by the 10-fold cross-validation method, the classifier will be trained and prepared for the online application. The Training parameters can be seen in Table 4 that contains learning rate (η), number of epochs (E), number of batch size (B), momentum (M), and activation function (γ). The outcome of the MLP classifier is shown in Table 5. As can be seen, the proposed method can accurately predict both SS and transient stability status of the power system 0.15 s after fault occurrence. In addition, these results indicate that the SGD optimizer leads to more accurate results.

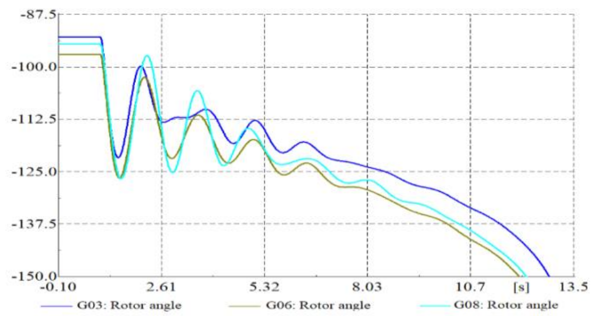

Fig. 6. An unstable study case in IEEE 14-bus network

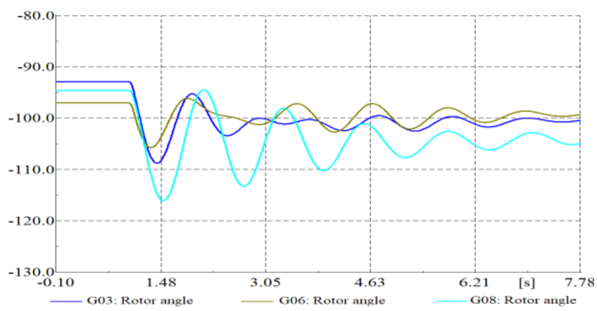

Fig. 7. A stable study case in IEEE 14-bus network

Table 4. The training parameters selected for IEEE 14-bus system

Model	η	E	B	M	γ
MLP	0.01	200	10	0.8	ReLU

Table 5. The result of MLP classifier against different optimizers in IEEE 14-bus test system

Optimizer	Classes	No. of cases	Accuracy
SGD	Normal	915	99.87%
	Alert	1209	
	Unstable	180	
Adam	Normal	915	99.74%
	Alert	1209	
	Unstable	180	
Adadelta	Normal	915	89.71 %
	Alert	1209	
	Unstable	180	

4.2. IEEE 39-bus test system

According to the method described in section 3, in this test system, there will be 4896 simulated study cases in the offline phase that include four types of short circuit events in three different locations of each line (34 lines) with six fault duration periods at two operating points. Then, the features set is calculated and used to train an MLP-based deep learning classifier whose results are given in Table 6. Also, the training parameters are shown in Table 7.

Table 6. The result of MLP classifier against different optimizers in IEEE 39-bus test system

Optimizer	Classes	No. of cases	Accuracy
SGD	normal	2052	99.24%
	alert	2394	
	unstable	450	
Adam	normal	2052	97.94 %
	alert	2394	
	unstable	450	
Adadelta	normal	2052	48.9 %
	alert	2394	
	unstable	450	

Table 7. The training parameters selected for IEEE 39-bus system

Model	η	E	B	M	γ
MLP	0.01	600	6	0.8	ReLU

According to these results, the proposed method can accurately predict both the SS and transient stability status of the test system. Also, similar to the classifier described in the previous subsection, these results show that the SGD optimizer leads to more accurate results.

4.3. Comparison of Results

While the methods proposed in the literature usually predict either transient or small-signal stability status, the method proposed in this manuscript can predict both transient and small-signal stabilities (the only method that considers both transient and SS stability is [15], where transient stability is predicted and SS stability is detected). In this respect, the results of the method proposed in this manuscript cannot be compared with the methods proposed in the literature. However, to evaluate the performance of the different methods, their precision has been mentioned in Table 8 which indicates that the proposed method can accurately predict both transient and small-signal stabilities.

Table 8. The accuracy of the different methods proposed for the rotor angle stability assessment

Ref.	Test system	Transient or SS	Accuracy
[10]	127 bus	Transient	97.3%
[16]	118 bus	Transient	86.13%
	145 bus	Transient	89.22%
[17]	39 bus	Transient	93.73%
	145 bus	Transient	96%
[18]	2100 bus	Transient	84.8%
[19]	39 bus	Transient	100%
[3]	39 bus	Transient	MSE = 1.2
[15]	39 bus	Transient (prediction) and SS (detection)	99.5%
	68 bus	Transient (prediction) and SS (detection)	97.22%
	145 bus	Transient (prediction) and SS (detection)	98.31%
Proposed method	14 bus	Transient (prediction) and SS (prediction)	99.87%
	39 bus	Transient (prediction) and SS (prediction)	99.24%

Also, it should be noted that (as mentioned in Table 1) the proposed method predicts the rotor angle stability against different types of faults (LLL, LL, LLG, and LG) at different fault locations.

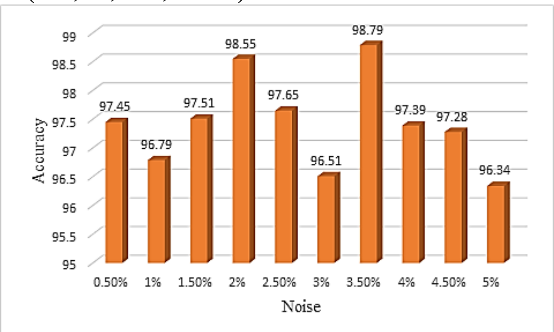

Fig. 8. The impact of the uncertainty of the measurements on the classifier accuracy

4.4. Impact of the uncertainty of the measurements

To analyze the impact of the uncertainty of the measurement (due to the measurement error, noise, etc.) the measured data which is used to train the MLP classifier has been randomly changed using a uniform distribution function. Then, the outcome variables are used to train a classifier whose results are given in Fig. 8. As shown, although such an uncertainty decreases the classifier's accuracy, the trained classifier still has acceptable performance.

5. CONCLUSION

Due to the high computational burden and complexity of the power systems, those methods exist in the literature that assess the rotor angle stability consider either the transient or small-signal stability. To overcome this deficiency, in this paper, by proposing a proper feature set, an MLP-based rotor angle stability prediction approach has been proposed to simultaneously predict both small-signal and transient stability status of the post-disturbance operating point. Since the proposed method does not need to calculate the generators' rotor angle (which requires a high computational burden) and requires only data measured by PMUs installed at generators' buses, it can timely predict the rotor angle stability and provide a proper chance for operators to take appropriate corrective measures.

The dynamic simulation results performed in IEEE14-bus and IEEE 39-bus test systems show that the proposed method can assess the stability stiffness and classify the post-disturbance operating point into Unstable, Alarm, or Normal categories with the precision of 99.87% (IEEE14-bus) and 99.24% (IEEE 39-bus), respectively.

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