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A proposed PMU-based voltage stability and critical bus detection method using artificial neural network

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Abstract

Voltage stability detection is currently still becoming the main issue in the modern integrated renewable energy power systems. To assess the voltage stability, the classical methods based on continuation power flow (CPF) technique were used to show nose curve. However, the classical methods require complete model of power system and long computation time. Data driven analysis and synchronized real time measurement technologies currently are developing in power systems monitoring, including the stability detection. The detection method is built based on the historical event model and uses the real time measurement as an input. For that reason, the algorithm to detect the voltage instability and critical bus is proposed using the artificial neural network (ANN) technique to represent the historical event model using the PMU measurement data. The ANN model architecture for this application is developed by creating seven hidden layers consisting of one normalization, four rectifier linear unit, one softmax and one sigmoid layer. To warrant the accuracy, the k-fold cross-validation is used. The algorithm is simulated on modified IEEE 14 test system which consider different loading scenario, line contingency, number of PMU and Photovoltaic (PV) integration. To mimic the actual historical data, the synthetic data is generated and labelled. The result shows that the proposed method can represent the complete power system model by giving high accuracy which for voltage stability detection is > 97% and critical buses detection is > 96% for all scenarios. Moreover, the required computation time is between 16 and 18 s per detection which makes the scalability to the real time detection is reasonable.

Keywords: Artificial neural network, Data driven model, Prediction accuracy, Voltage stability detection

Introduction

Power system stability still becomes one of the main problems in the power system due to the power system complexity. Stability detection is one of the most emerging issues in the power system area. Stability systems are important to ensure the power system fulfilling reliability, security, and economic criteria. Power system stability is the power system ability to come back to the equilibrium after suffering from disturbance as presented in Kundur et al. (2004). Stability in power system is classified as rotor angle

stability, voltage stability and frequency stability (Kundur et al. 2004). Commonly, to detect the stability two variables are required, voltage and frequency. Voltage stability problem occur because the power system operator tends to operate close to its limit (Putranto et al. 2017). Voltage stability is the ability of the power system to maintain the bus voltage in the permissible operation range after disturbance (Usman and Faruque 2019). Classical voltage stability assessment based on the CPF calculates the maximum loading point and measure with the current operating point (Kundur 1994). CPF produces the nose curves to assess the voltage stability which requires the complete model of the power system. The classical method requires power system network, power system operation point, line contingency status and the dynamic model of generating unit, load, and compensator. Furthermore, the model would be more complex if the preventive action (Capitanescu et al. 2007), corrective action (Capitanescu and Wehenkel 2008) and optimal operation (Zabaiou et al. 2014) are considered in the operation, which result the high computation burden. On the contrary, the short-term voltage stability problem due to the system dynamic would occur within the short-time frame (in second). For that reason, calculating CPF is not feasible in real time application due to the computation burden and requirement of complete model of the electrical system network as presented in Nazari-Heris et al. (2021).

Traditional real time monitoring is based on supervisory and control data acquisition (SCADA) which is updated every 2–10 s. SCADA uses power, power flow and voltage magnitude measurement to monitor and estimate power system operation condition. In SCADA, the voltage angle is estimated based on the measurement which are not synchronized as presented in Terzija et al. (2011). The short-term voltage stability needs accurate voltage angles information which may insufficient if only supported by SCADA. Power system utility upgrade the monitoring system with synchronized real time measurement using the phasor measurement unit (PMU) (Phadke 2002). PMU is not only able to measure the voltage angle but also has higher resolutions. This feature supports the real time monitoring in stability detection of power systems (Usman and Faruque 2019).

High data resolution provides sufficient information to perform the statistical analysis of a power system. For voltage stability case, voltage magnitude and angle can be a signature for the instability condition. When the event was sufficient, it can be built as database then the voltage stability detection based on the machine learning can be developed in a power system (Arghandeh and Zhou 2017). Using this kind of information, it is possible to perform early stability detection without requiring the complete model. The use of machine learning methods is generally divided into two steps; the first is generating and selecting features. The variable used as input for machine learning methods is the voltage phasor from the PMU. Second is the classification of the voltage stability margin (VSM) index (Alimi et al. 2020).

Voltage stability assessment using the line stability indexed was proposed in Yari and Khoshkhoo (2017). Four indexes there are line stability index (LSI), fast voltage stability indices (FVSI), line stability factor (LQP), and new voltage stability index (NVSI) were compared to give the assessment. For calculating the index, load flow analysis was simulated to generate the voltage magnitude information and power flow between lines. Simulation was executed in PowerFactory environment using the

DIgSILENT Programming Language. Simulation result showed that LSI and FVSI cannot provide accurate voltage stability status compared to LQP and NVSI.

One of the neural network methods is ANN (Haykin 1999). The use of ANN in voltage instability monitoring has been developed previously as presented in Zhou et al. (2010). In this research, the steady-state voltage magnitude and angle of the substations were selected as the input. In this research, the performance of the ANN method produces a small error, mean error from 0.1205% to 0.6528% and a maximum error from 0.6566% to 2.2614% which depends on the number of PMUs used. In this research, the required number of PMU to perform the proposed ANN was also investigated. Simulation in IEEE 39 bus test system results in smaller errors when using a larger number of PMUs or adding other measurement variables such as voltage magnitude and reactive power as inputs to the ANN. Using neural networks in classification can help efficiently analyze non-linear relationships between power system operating parameters and VSM, which are learned through voltage stability analysis (Zhang et al. 2013). Limitations of conventional methods are not considering the dynamic characteristics of electric power systems, requiring large amounts of computation, and not providing practical information about stability problems. The use of neural networks can deal with these limitations (Zhang et al. 2013).

Another ANN application was developed in Ashraf et al. (2017) to monitor voltage stability of power system using limited number of PMU. The network simplification was also used in this research. ANN predicted the maximum loading limit using the PMU measurement. Simulation was executed using IEEE 14 and 118 bus test system under MATLAB. There were internal and external area analysis from the sensitivity analysis to place where PMU should be located. The result showed that the maximum error of the ANN was between 0.055 until 0.4916%, showing that the simplification working well.

Random Forrest (RF) (Malbasa et al. 2017) and Feed Forward Based Propagation (FFBP) (Rumelhart et al. 1986) were simulated for voltage stability event classification on the simulated 10,147 operating point of WECC system. The offline training was simulated using 9147 sample while the online testing using 1000 sample. The result shown that RF has best result with 90.01% accuracy as presented in Malbasa et al. (2017). Support vector machine (SVM) approach for voltage stability detection was developed in IEEE 14 and 30 bus test system. The pattern of voltage stability and SVM parameter were done in the preprocessing stage. In the evaluation the fivefold validation was used with the accuracy of the detection reached 99% as presented in Pérez-Londoño et al. (2017). The probabilistic Decision Tree (DT) (Salzberg 1993) was developed to detect the voltage stability with 300 different load variations of IEEE 30 bus test system, including active, reactive power and contingency variations. This method was effective enough with 94% accuracy as presented in Nandanwar et al. (2018).

Static voltage stability assessment based on enhanced online RF algorithm has been proposed in Su and Liu (2018). Voltage magnitude and voltage angle were selected as the input to perform this method. This method proposed a novel method to update the tree to make the previous method more efficient. Online bagging and lead node splitting control were proposed to update the trees to prevent overfitting. The result showed that the proposed method can increase performance by 98.4%.

Real-time short-term voltage stability assessment was proposed in Pinzón and Colomé (2019) for the large disturbance. The proposed method was developed using data mining and machine learning with the time series voltage magnitude data from PMU. The proposed method was able to classify the power system status in some categories using maximal Lyapunov exponent calculation and dynamic index. The proposed method was simulated using IEEE 39 bus test system. The classification categories consisted of normal, alert, emergency, dan unstable. The RF algorithm was used as the machine learning technique. Some machine learning algorithms for voltage stability assessment were compared as presented in Adhikari et al. (2020). Gaussian Process Regression (GPR) (Williams and Rasmussen 1995), ANN (Haykin 1999), SVM (Pérez-Londoño et al. 2017; Vapnik 2000), and DT (Salzberg 1993) were compared in this research. The instantaneous steady-state voltage magnitude and angle from PMU data were used as input. Comparison was simulated under IEEE 39 bus test system which the GPR produces the highest accuracy.

Real time monitoring long term voltage stability assessment has been proposed in Dharmapala et al. (2020) using a voltage stability index. The proposed method predicted the loading margin to detect long term voltage stability. Power system operation data such as voltage, current and load flow from normal and contingency conditions were required in the data generation process. For generating the data CPF simulation was executed. The model was built for IEEE 14 and 118 buses test systems using RF regression. Voltage stability assessment using machine learning method which the data generation based on the CPF to calculate the VSM to determine the event is stable or not was presented in Mollaiee et al. (2021). DT, SVM, adaBoost (Freund and Schapire 1997), and bagged tree (Efron and Tibshirani 1986) are used for the computation algorithm. There is four data set combination there are voltage magnitude, voltage angle, active and reactive power set which were simulated in IEEE 39 and 118 bus test systems.

Real-time short-term voltage stability assessment using 1D-convolutional neural network (1D-CNN) with time series PMU data was proposed in Rizvi et al. (2021). There were two stages proposed in this method. The first stage detects fast voltage collapse based on 1D-CNN. The next stages then quantified the severity level of voltage instability. The proposed method was simulated on IEEE 30 and 39 buses test system under python environment. The proposed method uses post disturbance voltage information. In this method, the pre-processing data was also required to detect the data loss and outlier from PMU measurement. The summary state of the art of the research is presented in Table 1.

Based on the previous research on voltage instability detection, the critical bus location detection is added in the formulation. Some scenarios representing the normalization effect, PMU number, selection of PMU location, and renewable energy existence are developed in the proposed voltage stability detection. To create the database, the simulated power system operating points and the labels are required. The power system operating points are simulated using CPF in DIgSILENT PowerFactory under different scenarios to assess the system voltage static stability. The operating points then is labelled on voltage stability status and critical bus location. However, in the practical system, the collection of the operating points and labels database are recorded from the PMU measurement.

Table 1 State of the art of voltage stability detection

References	Year	Method	Stability detection	Critical Bus detection	PV Integration	Stability Type	input	Test case	Performance
Yari and Khoshkhoo (2017)	2017	Lmn, FVSI, LQP and NVSI	✓	–	–	Long-Term Voltage	Z, X, P, Q, V, θ, δ	9 bus	–
Zhou et al. (2010)	2010	ANN	✓	–	–	Long-Term Voltage	P, Q, V, θ	39 bus	Mean error: 0.1205–0.6528% Maximum error: 0.6566–2.2614%
Ashraf et al. (2017)	2017	ANN	✓	–	–	Long-Term Voltage	P, Q and/or V, θ	14 bus, 118 bus	Maximum error: 0.055–0.4916%
Pérez-Londoño et al. (2017)	2017	SVM	✓	✓	–	Long-Term Voltage	V, P, Q	14 bus, and 30 bus	Accuracy: 99.9%
Nandanwar et al. (2018)	2018	PFDT and CBR	✓	–	–	Long-Term Voltage	P, Q	30 bus	Accuracy: 94%
Su and Liu (2018)	2018	Random Forest	✓	–	–	Long-Term Voltage	P, Q, V, θ	57 bus, Taiwan Power System (1821 bus)	Accuracy: 94.8–99.9%
Pinzón and Colomé (2019)	2019	Random Forest	✓	–	–	Short-Term Voltage	V	39 bus	Mean error: 1.697–2.033%
Adhikari et al. (2020)	2020	Gaussian Process Regression, ANN, SVM, DT	✓	–	–	Long-Term Voltage	V, θ	39 bus	MSE: 0.568–14.37%
Dharmapala et al. (2020)	2020	Random Forest	✓	–	–	Long-Term Voltage	Z, P, Q, V, θ, δ	14 bus, 118 bus	RMSE: 0.61–5.07%
Mollaiee et al. (2021)	2021	DT, SVM, AdaBoost, Bagged Tree	✓	–	–	Long-Term Voltage	P, Q, V, θ	39 bus, 118 bus	Accuracy: 69–96.02%
Rizvi et al. (2021)	2021	1D-CNN	✓	✓	–	Short-Term Voltage	V	30 bus, 39 bus, 118 bus	Accuracy: 92–100%
Proposed	2023	ANN	✓	✓	✓	Long-Term Voltage	V, θ	14 bus	Accuracy: > 96%

The detection is developed under the modified ANN model by creating seven hidden layers consisting of one normalization, four rectifier linear unit, one softmax and one sigmoid layer. To warrant accuracy, the k-fold cross-validation is used. As the input, instantaneous PMU data is required. The voltage angle and magnitude information are required from PMUs. The detection and classification are formulated based on ANN which are simulated under python environment. The accuracy of the proposed detection method is higher than 96% as presented in Table 1.

Materials and methods

The ANN detection method will use the PMU measurement data from the power system. The IEEE 14 bus test systems is used as the test case with a different number of PMU, loading and contingency variations as presented in test case subsection. Those scenarios are simulated and considered as data generation, which will be used as historical data presented in data generation subsection. Each simulated data then labelled into stable or unstable condition, including the critical bus information. The mathematical ANN detection model to detect the voltage instability and critical bus is formulated in the model formulation subsection.

Test case

To demonstrate the effectiveness of the detection method, the model would be tested in modified IEEE 14 bus presented in Fig. 1. There are two topologies tested in the simulation to show the effect of PV integration in the test systems. First, there is no PV generating unit in the test system and second there is PV generating unit in bus number 3.

In those test systems, there are 5 generating unit with the total capacity 700 MW, 11 load center, 14 buses, 16 lines, 5 transformer and 1 shunt compensator. There are four voltages levels 132, 33, 11 and 1 kV. The system's total load is 259 MW and 73.5 MVAR. The IEEE test system data were presented in DIgSILENT GmbH (2020). The PV generating unit is modeled as constant power with unity power factor with 50 MWp penetration which is 20% of system total load. There are some PMU installed in the test system with the number of PMU is vary to identify the effect on the accuracy.

Computer specification

The specifications of the computer used in this study to simulate data generation and build the deep learning model are shown in Table 2. In addition, the main software used in the simulation includes PowerFactory 2022 SP4, Python 3.9.12, and TensorFlow 2.10.

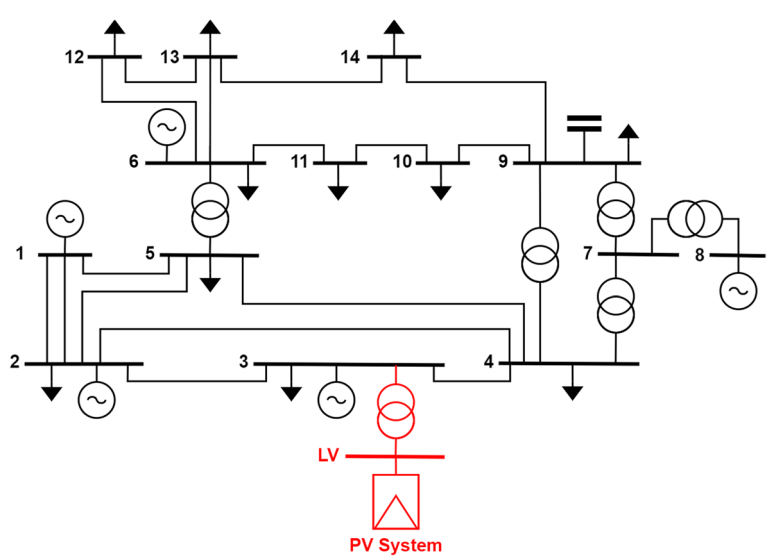

Fig. 1 Modified IEEE 14 Bus System Single Line Diagram (DIgSILENT GmbH 2020)

Table 2 Computer specification

Specification	Description
Processor	2.80 GHz
System type	64-bit, × 64-based processor
Storage	512 GB
Memory	16.0 GB

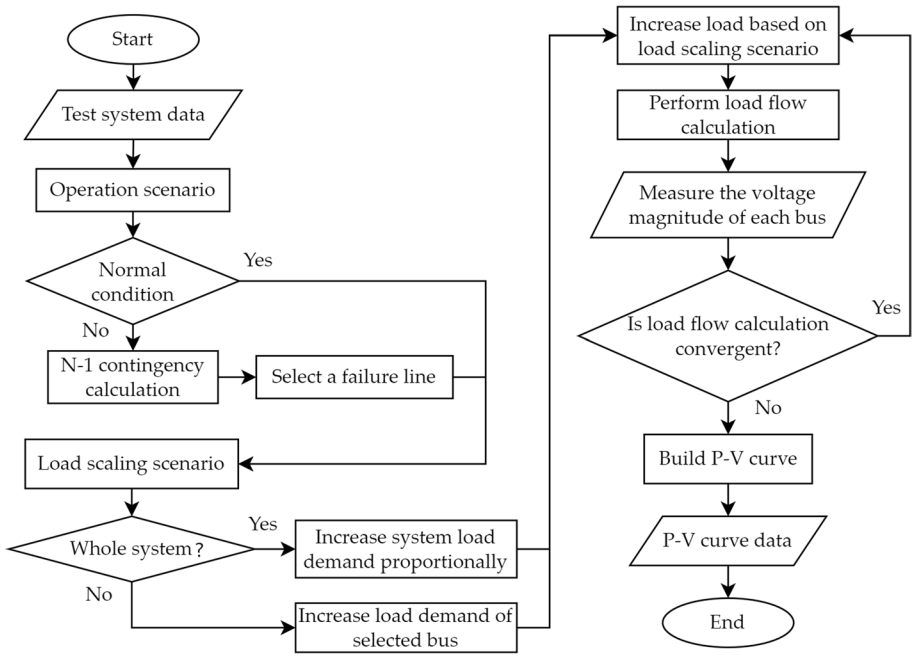

Fig. 2 Generation of nose curve data based on the continuation power flow

Data generation

The data synthetic of power system operation is generated using power system analysis especially the CPF. There are two main operation scenarios based on PV integration, without and with PV integration. The data generation for those two main scenarios are presented in Fig. 2. The nose curve is calculated by obtaining the critical node by increasing the active power in the selected bus until the load flow calculation is not convergent as presented in Kundur (1994); DIgSILENT GmbH 2020). The output of this process is the set of nose curve data.

There are variations of load scaling, line contingency and number of PMUs for those two scenarios. The load scaling variations are simulated in the whole buses simultaneously and in an individual bus. In the whole buses, the load will proportionally increase up to the unstable condition while in an individual bus the load increment only occur in that respective bus.

In line contingency condition, the power system operation would be very different from the normal condition so that the operating data need to be generated for every single line contingency. Each operating condition in the nose curve trajectory would be

the raw data for the labelling process. The CPF would be executed for each scenario by increasing the load continuously so that the critical point (Karki 2009) would be reached and the power flow in that operating condition is not convergent. The critical point is also called nose curve which is used as the reference in the labelling process. The nose curve is also called P–V curve which shows the active power and the corresponding voltage during CPF.

To assess the voltage stability of the system, the stable and unstable region in the nose curve area should be defined as presented in Fig. 3. The stable operating condition is in the green color and the unstable condition is red color. Between the areas there is a vertical dashed line to limit the stability border which is set 90% distance from the nose curve. The blue dots reflect all the possible operating points in the trajectory to the collapse point. In the real time application, the measured voltage operating point in high resolution is very important of which PMU is capable of.

The real unstable condition is in the nose curve which in this state the system has already collapse. However, in this study the unstable region is define in 90% from the critical point as presented in reference (Putranto et al. 2017), to give the system operator warning that the power system is going to collapse. The labelling process is presented in Fig. 4, which the stability margin and the critical buses are labeled. The stable condition is set up to 90% of nose curve and the critical buses is the lowest bus voltage close to the nose point. In this process, each operating point of all scenarios would be used as the input data with the nose curve of each scenario considered as the references. There would be two classes that are stable and unstable. Another information is the critical busses, it is the busses with the minimum voltage at the nose curve.

Model formulation

The data preparation, model formulation and stability detection are proposed in this section. Generally, the workflow of the model formulation is presented in Fig. 5. There are three parts in the model formulation that are formulation of ANN architecture, hyperparameter tuning and cross-validation.

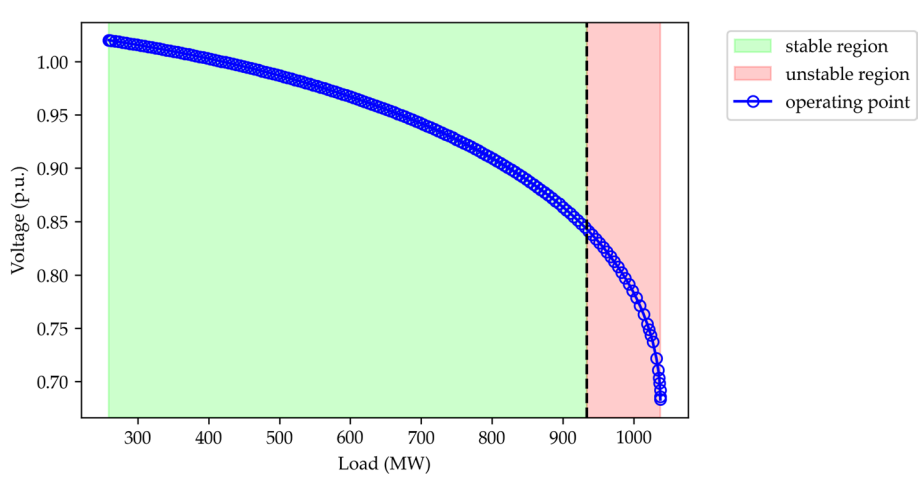

Fig. 3 Illustration of stable and unstable region of voltage stability (Putranto et al. 2017)

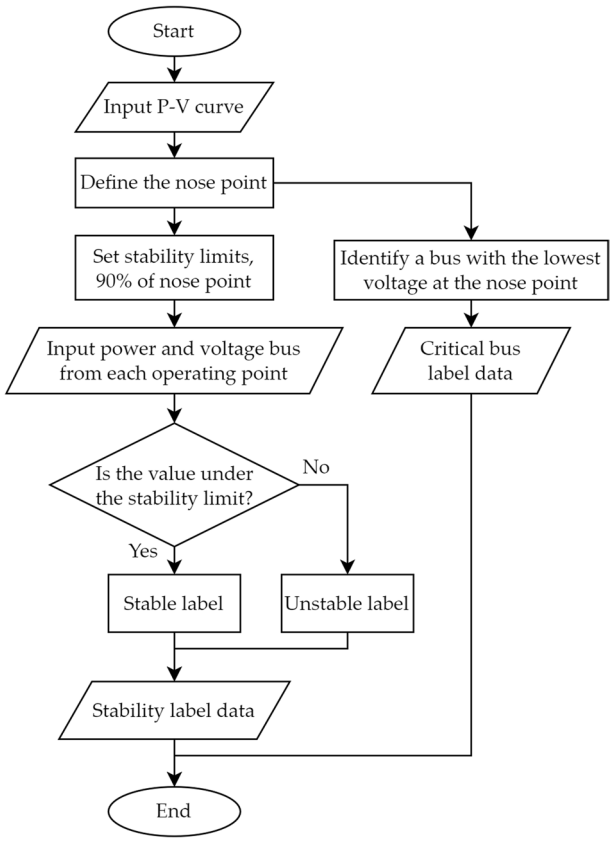

Fig. 4 Voltage stability status data labelling

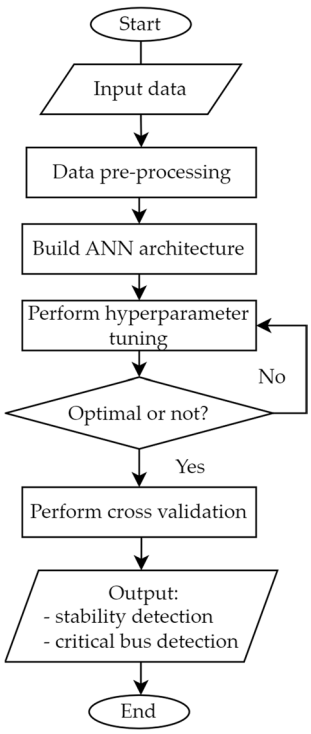

Fig. 5 Model formulation workflow

ANN architecture is built by defining the input layer hidden layer and output layer. The shape of ANN architecture is presented in Fig. 6. In this research the input data is the 1xn voltage magnitude vector with n is the bus number of the input data. Currently, the high resolution of buses voltage magnitude is measured by PMU. If the PMU is installed in all buses that would be ideal condition since all of buses can be measured at the time stamp. In this research, the number of PMU effect on the accuracy would also be investigated. The output of the method would be two branches that are voltage stability detection and critical bus location. Critical bus detection includes the multiclass classification since there are more than two buses as the target. For that purpose, the bus locations need to be transformed for the calculation purpose. There is a technique called one-hot encoding to transform the class output into binary vector with 0 and 1 as presented in Al-Shehari and Alsowail (2021). One value would be the identity of the defined classes, otherwise zero.

There are seven layers used in the ANN architecture other than input and output. The first layer is the normalization layer which is useful for normalizing each data feature column. The robust scaler technique would cancel the median and scale the data based interquartile range. Interquartile range is the range between first and third quartile. This normalization is done to transform data in the different column feature so that it has the same scale and robust to the outlier. The normalization is done by reducing data with the first quartile from several samples divided by interquartile range sample in each column feature data. In this research, the effect on the stability detection dan critical bus location accuracy when the data normalization is done or not. The mathematical formulation is presented in the Eq. (1) (Ayub and El-Alfy 2020) as follow:

$$x_{i,j'} = \frac{x_{i,j} - Q_{1j}}{Q_{3j} - Q_{1j}} \tag{1}$$

where $x_{i,j}$ is the data on the sample-i and feature-j, Q_{1j} is the first quartile of feature-j, Q_{3j} is the third quartile of feature-j, and $x_{i,j'}$ is the normalized data. In the dense layer,

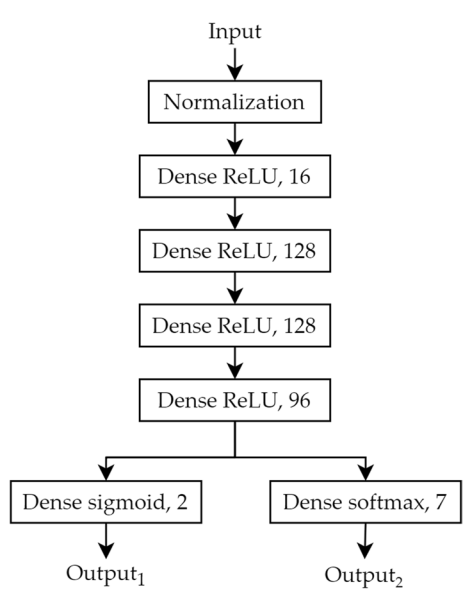

Fig. 6 Proposed ANN architecture

the activation function would be operated which the mathematical formulation is shown in the Eq. (2) (Khan et al. 2018) as follow:

$$y = f_{activation}(\boldsymbol{W} \bullet x + b) \tag{2}$$

where $\boldsymbol{W}$ is the weighted matrix, x is the vector input, b is the bias vector, $f_{activation}(\bullet)$ is the activation function, and y is the output vector output dense layer. Activation function is used to produce the nonlinearity so that the classification can be done. In this research, dense layer uses the rectifier linear unit (ReLU) (Fukushima 1969). ReLU function will map the input to 0 if the value is negative and not change if positive. The mathematical formulation of the ReLU is in Eq. (3) (Khan et al. 2018) as follow:

$$f_{ReLU}(x) = \max(0, x) \tag{3}$$

The number of units in the first dense layer is determined by hyperparameter tuning. Hyperparameter tuning is calculated using Bayesian Optimization with the Gaussian process which do the loss minimization. The next layer is the dense layer with the sigmoid and softmax activation function. Dense layer with the sigmoid activation function is used to map the input into binary value. While softmax is used to map the input into the Gaussian probability distribution in range 0 to 1. Sigmoid activation function is used to do binary classification, while softmax for multiclass classification. The mathematical formulation of those two functions are presented in Eqs. (4) (Von 2007) (Khan et al. 2018) and (5) (Dzulqarnain et al. 2019) as follows:

$$f_{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

$$f_{softmax}(x) = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_j}} for i = 1, 2, \ldots, k \tag{5}$$

Moreover, for assessing the accuracy of the prediction, the loss function is used. There are two loss functions used in the detection method that are loss binary cross entropy and loss categorical cross entropy function. Loss binary cross entropy function is used to measure the binary classification while loss categorical cross entropy function is used for multiclass. The mathematical formulation of those two functions is presented in Eqs. (6) and (7) (Azhar et al. 2022) as follow:

$$loss_{binary} = -t_i log\left(y_i\right) - (1 - t_i) log(1 - y_i) \tag{6}$$

$$loss_{categorical} = -\sum_{i=1}^{l} t_i log\left(y_i\right) \tag{7}$$

where t_i is the class target in the element-i, y_i is the prediction output model in element-i, and l is the bit number of the one-hot encoding result. To get the most accurate ANN model, the minimization of the loss function in the training process can be done. In this research, the adaptive moment estimation (ADAM) is used (Kingma and Ba 2014). ADAM has advantages of a fast-learning rate and require less computation

time. So that, ADAM is suitable for non-stationery and gradient which is very noisy and sparse (Soydaner 2020).

After the model architecture and hyperparameter value is formulated, the model is tested using cross-validation. Cross-validation is the data resampling method to assess the generalization capability and to avoid overfitting. In the k-fold cross-validation, the available training set learning is divided into k partition in the same size. Fold relates to the number of partitions which produced from the process as presented (Berrar 2019). The stratified k-fold cross-validation is used in the proposed method with the number of k is 10. The stratified random sampling which divides the class so that the proportion in the individual set reflects the proportion in the learning set is used in the cross validation. So that, each class label has the same number of proportions in each fold (Berrar 2019; Prusty et al. 2022). The number of k is 10 which is the recommendation from the previous research as presented in Kohavi (1995).

Simulation results

In the section, the nose curve generation, data labelling, hyperparameter tuning and cross-validation are discussed. Moreover, the variation of line contingency, load scaling, and data normalization on PV integration scenarios are formulated as presented in Table 3. There would be 51 variations for without PV and 52 variations for with PV integration which reflected the number of nose curve. The data generation of nose curve is simulated using DIgSILENT PowerFactory while Python is used to vary the scenario and run the process fully automatic. Then the proposed model is built under python environment.

Nose curves generation and data labelling

Some of nose curve data generations sample are presented in Figs. 7, 8, 9, 10. The figure shows the CPF result for each bus of modified IEEE 14 buses test system with the x axis tells the total capable system load that the network can handle, while the y axis is the voltage magnitude. Those figures show the nose curve area which shows the stability margin of the system operation. The green area shows the stable area which is up to 90% from the nose curve while red area shows the unstable region.

In that figures, load scaling in non-contingency condition without PV in Fig. 7, with PV in Fig. 8, load scaling in line 2–3 contingency condition without PV in Fig. 9 and

Table 3 Variations of power system operating conditions

Parameter	Scenarios	
	Without PV	**With PV**
Load scaling	Whole system, only Load 3, and only Load 9	Whole system, only Load 3, and only Load 9
N-1 contingency	Normal condition	Normal condition
	Each of the 16 lines	Each of the 16 lines
	–	PV system in Bus 3
Variation number of PMUs	5, 7. 9 and 14	5, 7. 9 and 14
Normalization effect	With and without normalization	With and without normalization

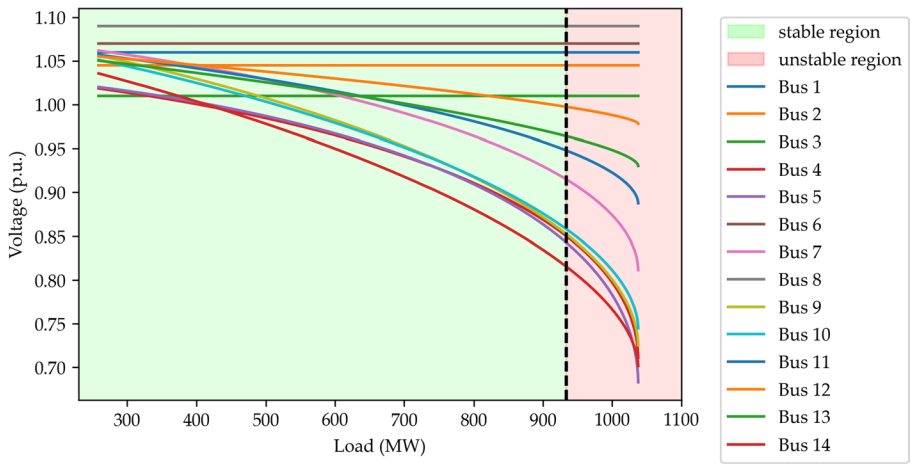

Fig. 7 Nose curve generation results in without PV system scenario with all loads scaling and no contingency

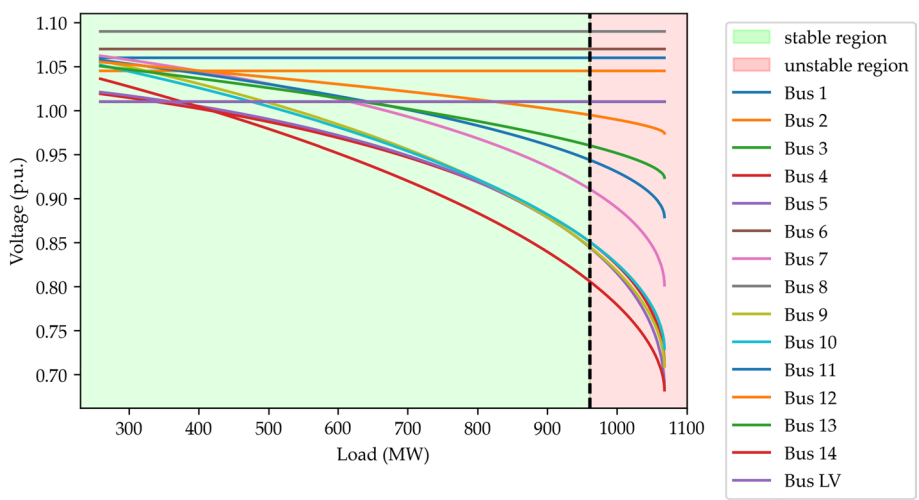

Fig. 8 Nose curve generation results in with PV System scenario with all load scaling and no contingency

with PV in Fig. 10. The critical buses are in bus 5, bus 5, bus 4 and bus 4 with the nose point 1037.7, 1068.1, 588.5 and 671.1 for the scenario a, b, c and d, respectively. Integration of PV generating unit seem gives the positive impact to the system stability, if we compared the scenario Figs. 7, 8, 9, 10, which gives the PV integration topology better nose point.

The pair of 14 bus voltage on each operation loading condition would be used as the input data. For 51 without PV scenarios, there are 13,107 data rows of 14 buses. While for 52 with PV scenarios, there are 13,839 data rows of 14 buses. Each row is a 1×14 vector consisting of voltage magnitude data. Those data rows would also be labelled with the voltage stability status and critical bus location. They also provide many trajectories options to represent in which state the power system would operate for the near time step. The labelled 13,107 data rows for without PV and 13,839 data rows with PV are used for the data input in the proposed ANN model.

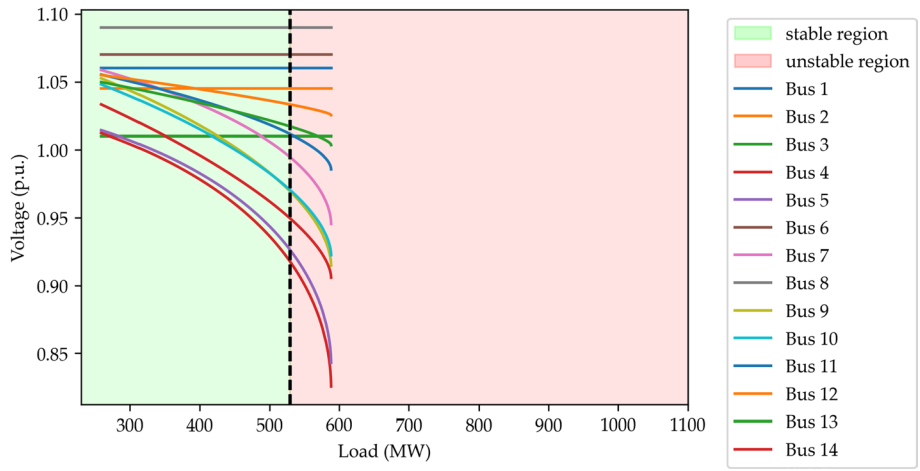

Fig. 9 Nose curve generation results in without PV system scenario with all loads scaling and contingency in line 2–3

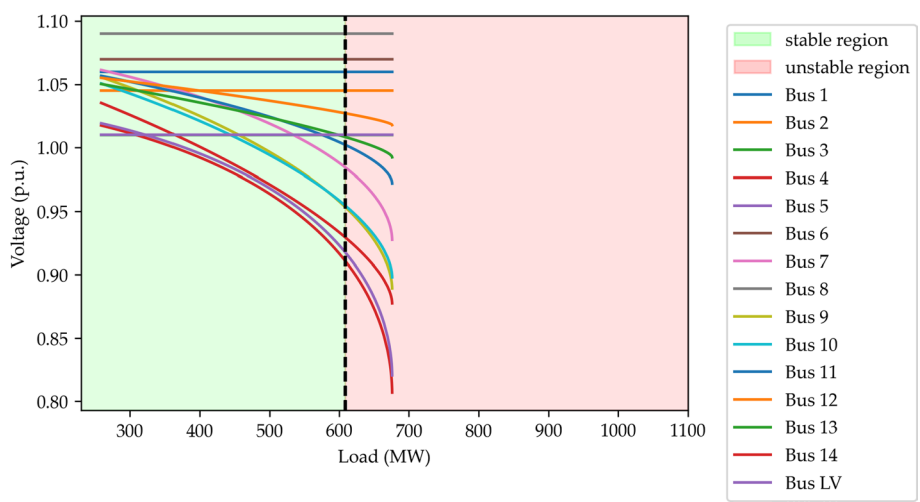

Fig. 10 Nose curve generation results in with PV system scenario with all loads scaling and contingency in line 2–3

Hyperparameter tuning results

The hyperparameter tuning processes are done by trying some possible combination which has the minimum score of loss. The top 10 combination of the best trial result is presented in Table 4 and Table 5 for without and with PV scenario, respectively. Generally, more unit in the layer will result in better ANN training. However, more units can also cause overfitting. One of the examples is in the rank 1 and rank 6, which in the first dense in rank 1 is less than rank 6 but the loss score of rank 1 is better than rank 6. In that case, the rank 6 combination has suffered the overfitting. Based on the trial, the number of units in each dense layer of both PV scenario are 16, 128, 128 and 96, respectively for first to fourth layer.

Table 4 Top 10 best trial results on the hyperparameter tuning process in without PV scenario

Rank number	Layer				Loss score
	First dense	Second dense	Third dense	Fourth dense	
1	16	128	128	96	0.15455
2	16	64	128	96	0.15584
3	32	96	128	96	0.15728
4	64	64	128	96	0.15772
5	32	128	96	96	0.15829
6	64	128	128	96	0.15959
7	32	96	64	64	0.16183
8	16	64	64	96	0.16708
9	16	128	128	32	0.16812
10	64	64	64	32	0.17221

Table 5 The 10 best trial results on the hyperparameter tuning process in with PV scenario

Rank number	Layer				Loss score
	First dense	Second dense	Third dense	Fourth dense	
1	16	128	128	96	0.159781
2	32	128	128	96	0.167234
3	32	128	96	96	0.168303
4	16	128	112	96	0.168811
5	16	128	128	32	0.173575
6	64	128	128	96	0.174498
7	16	128	128	80	0.176799
8	64	128	64	96	0.183777
9	32	96	64	64	0.185018
10	16	64	128	96	0.189285

Impact of normalization

The normalization effect in the pre-processing stage is presented in this section. The simulation uses 10 folds cross-validation to detect the stability status and critical bus location. The cross-validation result of without PV systems is presented in Table 6. In this scenario, the highest accuracy in the stability detection without normalization is 97.25% in fold 10, while with normalization is 99.01% in fold 10. Moreover, for critical bus detection the highest accuracy without normalization is 90.16% in fold 2, while with normalization is 97.56% in fold 4. Furthermore, the mean value for stability detection is $96.47 \pm 0.70\%$ (without normalization) and $98.04 \pm 0.51\%$ (with normalization) while for critical bus detection are $86.22 \pm 3.85\%$ (without normalization) and $96.90 \pm 0.38\%$ (with normalization). Normalization surely has a positive impact in the accuracy especially for critical bus detection. There is occur due to the outlier in the data set as presented in Fig. 11. With the robust scaler normalization in data pre-processing process, the outlier can be neglected.

On the other than, the cross-validation for with PV scenario is presented in Table 7. In this scenario, the highest accuracy in the stability detection without normalization is 97.18% in fold 4, while with normalization is 99.13% in fold 4.

Table 6 Cross-validation results in without PV scenario for impact of normalization test

Fold number	Accuracy (%)			
	Without normalization		With normalization	
	Stability	Critical Bus	Stability	Critical Bus
1	96.49	87.95	97.48	96.72
2	97.03	90.16	97.71	97.10
3	95.96	87.95	98.40	97.18
4	97.03	85.51	98.25	97.56
5	95.88	87.34	97.25	96.49
6	96.80	83.75	97.94	96.19
7	94.81	76.13	98.63	97.10
8	96.87	88.55	97.86	96.64
9	96.56	89.54	97.86	96.87
10	97.25	85.27	99.01	97.10
Mean	96.47	86.22	98.04	96.90
Standard deviation	0.70	3.85	0.51	0.38

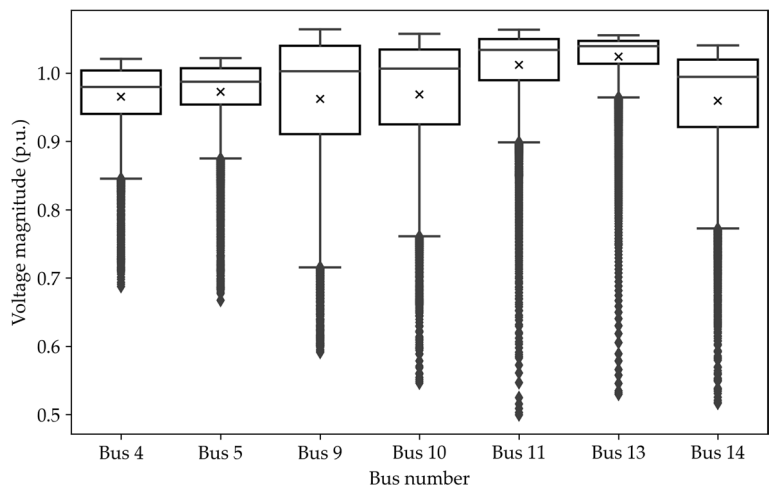

Fig. 11 Boxplot of the dataset used in without PV system scenario

Moreover, for critical bus detection the highest accuracy without normalization is 89.38% in fold 9, while with normalization is 97.69% in fold 10. Furthermore, the mean value for stability detection is $96.34 \pm 0.59\%$ (without normalization) and $98.36 \pm 0.36\%$ (with normalization) while for critical bus detection are $86.05 \pm 3.56\%$ (without normalization) and $96.81 \pm 0.48\%$ (with normalization). The result on with PV scenario show the same trends as without PV scenario which the normalization can neglect the outliers in Fig. 12.

The required simulation time of normalization impact in each scenario is shown in Table 8. With PV scenario results in higher time simulation than without PV scenario since with PV scenario has a larger number of data rows.

Table 7 Cross-validation results in with PV scenario for impact of normalization test

Fold number	Accuracy (%)			
	Without normalization		With normalization	
	Stability	Critical Bus	Stability	Critical Bus
1	95.74	84.03	98.63	96.89
2	95.38	82.30	98.48	96.53
3	95.66	88.37	98.05	97.25
4	97.18	89.02	99.13	96.32
5	96.89	88.95	97.76	96.97
6	96.60	89.23	98.48	97.04
7	96.68	85.98	98.48	97.04
8	96.17	78.03	97.98	96.46
9	96.10	89.38	98.27	95.95
10	97.04	85.25	98.34	97.69
Mean	96.34	86.05	98.36	96.81
Standard deviation	0.59	3.56	0.36	0.48

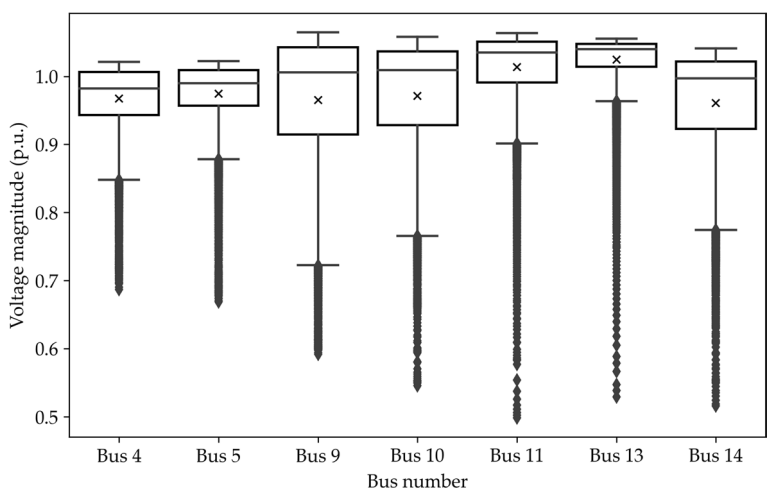

Fig. 12 Boxplot of the dataset used in with PV system scenario

Impact of the number of PMUs

In the real time application, PMU will be used to measure the real time bus voltage. However, the PMU investment cost is high so that for economic reasons the PMUs are only install in several buses. In the real time application, the direct voltage measurement is taken from the PMU and run in the model in the data center every period. The period can be flexibly set since PMUs have high sampling resolution and synchronized between each unit. In this part the effect on the accuracy under different number of PMUs are presented for with and without PV scenario.

The number of PMUs varies form 5, 7, 10 and 14 units. The model is simulated using cross-validation method with 10 folds. The cross-validation result of the PMU number variation is presented in Table 9. For 5 number of PMUs, the location is in buses 4, 5, 9, 11 and 13. For 7 number of PMUs, the location is in buses 4, 5, 9, 10, 11,

Table 8 The required simulation time of the normalization test

Fold number	Time (s)			
	Without normalization		With normalization	
	No PV	PV	No PV	PV
1	16.37	17.93	17.17	17.81
2	16.59	17.44	16.51	17.23
3	16.98	17.43	16.75	17.67
4	16.95	17.29	16.78	16.85
5	16.02	17.52	16.22	17.88
6	16.89	17.56	15.82	17.62
7	16.91	17.64	16.42	17.38
8	15.62	17.33	16.68	17.57
9	16.84	17.84	16.89	17.47
10	16.79	17.85	16.33	16.58
Mean	16.60	17.58	16.56	17.41
Standard deviation	0.43	0.21	0.36	0.40
Total	165.96	175.82	165.58	174.07

Table 9 Cross-validation results in without PV scenario for impact of the number of PMUs test

Fold number	Accuracy (%)							
	5 PMUs		7 PMUs		10 PMUs		14 PMUs	
	Stability	Critical Bus	Stability	Critical Bus	Stability	Critical Bus	Stability	Critical Bus
1	97.64	96.41	97.48	96.72	96.64	96.34	97.94	97.1
2	97.94	97.56	97.71	97.10	98.47	97.79	97.86	97.79
3	98.32	97.33	98.40	97.18	98.4	97.48	98.32	96.8
4	98.25	95.27	98.25	97.56	98.32	97.71	98.17	95.88
5	98.86	97.18	97.25	96.49	97.56	95.19	97.48	97.25
6	98.47	95.73	97.94	96.19	98.55	96.95	97.79	96.64
7	98.86	96.19	98.63	97.10	98.7	97.79	98.47	97.64
8	98.02	96.87	97.86	96.64	98.09	97.25	98.09	97.18
9	97.33	97.63	97.86	96.87	98.17	97.33	97.48	98.24
10	98.63	96.18	99.01	97.10	98.55	97.33	98.78	97.71
Mean	98.23	96.64	98.04	96.90	98.15	97.12	98.04	97.22
Standard deviation	0.48	0.76	0.51	0.38	0.59	0.76	0.40	0.64

13 and 14. Then for 10 number of PMUs, the location is in buses 1, 4, 5, 7, 9, 10, 11, 12, 13 and 14. From all possible combination scenarios, there are 7 variations of critical busses which are in buses 4, 5, 9, 10, 11, 13 and 14. The PMU location is intentionally located to cover those variations.

In this scenario, the highest accuracy of stability detection for 5 PMUs is 98.86% in fold 5, 7 PMUs is 99.01% in fold 10, 10 PMUs is 98.70% in fold 7, and 14 PMUs is 98.78 in fold 10. While for the critical bus location detection for 5 PMUs is 97.63% in fold 9, 7 PMUs is 97.56% in fold 4, 10 PMUs is 97.79% in fold 2 and 14 PMUs is 98.24% in fold 9. For mean and the standard deviation of the stability detection, for 5 PMUs is 98.23 ± 0.48%, 7 PMUs is 98.04 ± 0.51%, 10 PMUs is 98.15 ± 0.59%, and 14 PMUs is 98.04 ± 0.40%.

While for critical bus detection, for 5 PMUs is 96.64 ± 0.76%, 7 PMUs is 96.90 ± 0.38%, 10 PMUs is 97.12 ± 0.76%, and 14 PMUs is 97.22 ± 0.64%. Based on the simulation, there are no significant difference in accuracy under different number of PMU.

The cross-validation simulation result of the PMU number effect with PV integration is presented in Table 10. The PMU location is the same as in the without PV scenario.

In this scenario, the highest accuracy of stability detection for 5 PMUs is 98.63% in fold 5, 7 PMUs is 99.13% in fold 4, 10 PMUs is 98.77% in fold 3 and 14 PMUs is 98.55 in fold 2. While for the critical bus location detection for 5 PMUs is 97.25% in fold 3, 7 PMUs is 97.69% in fold 10, 10 PMUs is 97.98% in fold 2, and 14 PMUs is 97.76% in fold 8. For mean and the standard deviation of the stability detection, for 5 PMUs is 98.16 ± 0.61%, 7 PMUs is 98.36 ± 0.36%, 10 PMUs is 98.08 ± 0.37%, and 14 PMUs is 98.10 ± 0.61%. While for critical bus detection, for 5 PMUs 95.76 ± 1.47%, 7 PMUs is 96.81 ± 0.48%, 10 PMUs is 97.26 ± 0.52%, and 14 PMUs is 96.66 ± 0.86%. Based on the simulation, there are no significant differences in accuracy under different number of PMUs and the PV integration scenario. The required simulation time of different number of PMUs in each scenario is presented in Table 11.

Discussion

Voltage stability detection and monitoring application has been presented in previous research. However, most of the application is built based on network topology information, power system operation condition, system dynamic model, state estimation and power system analysis which require complete model of the power system and high computation burden in near real time applications. Currently, the data driven analysis based on the historical data is also developed into many applications especially in system stability analysis. If the historical data can be formulated into the representative model, the application would represent the complete model of the power system.

Table 10 Cross-validation results in with PV scenario for impact of the number of PMUs test

Fold number	Accuracy (%)							
	5 PMUs		7 PMUs		10 PMUs		14 PMUs	
	Stability	Critical Bus	Stability	Critical Bus	Stability	Critical Bus	Stability	Critical Bus
1	98.55	96.6	98.63	96.89	97.83	97.62	98.41	96.68
2	98.34	97.04	98.48	96.53	98.05	97.98	98.55	97.04
3	97.62	97.25	98.05	97.25	98.77	96.68	97.54	97.04
4	98.55	96.68	99.13	96.32	98.55	96.89	98.48	96.82
5	98.63	93.64	97.76	96.97	97.9	97.33	98.34	97.11
6	98.05	92.7	98.48	97.04	98.05	97.62	96.53	94.51
7	98.34	94.65	98.48	97.04	98.19	97.04	98.41	96.68
8	98.41	96.68	97.98	96.46	98.27	97.83	97.83	97.76
9	98.55	96.32	98.27	95.95	97.83	97.4	98.41	97.18
10	96.53	96.02	98.34	97.69	97.4	96.24	98.48	95.81
Mean	98.16	95.76	98.36	96.81	98.08	97.26	98.10	96.66
Standard deviation	0.61	1.47	0.36	0.48	0.37	0.52	0.61	0.86

Table 11 The required simulation time of the PMUs number variation

Fold number	Accuracy (%)							
	5 PMUs		7 PMUs		10 PMUs		14 PMUs	
	No PV	PV	No PV	PV	No PV	PV	No PV	PV
1	17.22	17.30	17.17	17.81	16.70	17.20	16.65	17.26
2	17.13	17.07	16.51	17.23	16.21	17.20	16.39	17.15
3	16.56	17.36	16.75	17.67	16.78	17.01	16.72	17.74
4	16.60	17.09	16.78	16.85	16.56	18.27	16.84	17.36
5	17.35	17.45	16.22	17.88	16.26	18.55	16.25	17.02
6	17.11	17.89	15.82	17.62	17.35	18.22	16.96	17.15
7	16.29	18.18	16.42	17.38	16.29	17.38	17.23	16.77
8	17.20	17.66	16.68	17.57	16.88	17.11	16.09	17.00
9	16.68	17.38	16.89	17.47	16.49	17.35	17.18	18.59
10	17.28	17.75	16.33	16.58	16.38	17.78	16.54	17.59
Mean	16.94	17.51	16.56	17.41	16.59	17.61	16.68	17.36
Standard deviation	0.35	0.34	0.36	0.40	0.33	0.53	0.36	0.49
Total	169.44	175.14	165.58	174.07	165.91	176.09	166.84	173.62

The data driven for power system application is supported by the existence the synchronized measurement which can be provided by PMU. PMU has the capability to measure the voltage phasor in high resolution up to 60 data per minute. When the model exists, the data from the PMU is used as the main input. In this application, the instantaneous data from installed PMUs are used to predict the stability and critical bus location. From the simulations, it can give high accuracy of the detection which for every scenario is above 96%. In this case the proposed method can represent the complete power system model.

For supporting the effectiveness of the proposed model, the set data operation to show the voltage stability status and the critical buses is needed. In this research, the historical data is provided by performing data synthetic procedure which the pair of voltage magnitude, loading conditions and voltage stability status is needed. For that purpose, representative operating condition is generated by varying the bus loading, network topology change and PV integration. The CPF is then simulated so that the pair of the operating point and stability status can be labelled. Furthermore, the variation of unstable voltage and critical bus location is well defined so that the information for PMU placement is clear. In the 5, 7 and 9 PMUs variations, the detections are still accurate since PMUs can cover critical bus and credible contingency.

For another perspective, when the location of critical bus information is unknown, the PMU placement needs to be considered before the implementation. In example, if the PMU location is randomly change, it will affect in the accuracy. For comparison, there are four set of PMU location for 5 PMUs. The original set (set 1) which is used in the main simulation, PMU are located at 4, 5, 9, 11 and 13. Other combinations are namely set 2, set 3 and set 4, where the PMUs at set 2 are located at 1, 4, 7, 11 and 14, set 3 at 2, 5, 6, 10 and 13 and set 4 at 3, 6, 9, 10 and 14. Different combinations result in different detection accuracy as presented in cross-validation in Table 12.

Table 12 Cross-validation results in without PV scenario for impact of PMUs selection

Fold number	Accuracy (%)							
	Set 1		Set 2		Set 3		Set 4	
	Stability	Critical Bus	Stability	Critical Bus	Stability	Critical Bus	Stability	Critical Bus
1	98.4	96.87	97.94	95.58	97.94	93.97	93.82	84.21
2	98.4	97.1	98.09	97.64	98.32	95.58	93.21	85.43
3	98.47	97.86	98.63	96.49	98.02	94.05	93.14	84.82
4	98.7	96.8	98.32	97.1	97.79	95.35	92.91	83.83
5	97.33	94.36	98.93	96.64	98.02	93.97	93.44	83.52
6	98.25	96.34	98.86	94.74	97.94	95.8	93.21	83.14
7	98.86	97.64	98.63	96.34	97.64	93.9	93.36	84.29
8	97.33	96.64	97.94	96.34	96.79	92.44	92.44	82.14
9	97.33	96.56	98.02	95.73	97.63	94.81	94.05	83.66
10	98.4	97.4	98.47	96.49	97.94	94.89	93.13	83.74
Mean	98.15	96.76	98.38	96.31	97.80	94.48	93.27	83.88
Standard deviation	0.56	0.92	0.36	0.77	0.39	0.96	0.43	0.86

The proposed detection method is built using the ANN model which has seven hidden layers which has been developed based on PMUs data. The model is successfully predicting the voltage stability and critical buses using synthetic data. The scalability to the larger system can be applied as long as the number of PMUs is sufficient to cover the critical buses, credible line contingency and load variations. Dealing with the actual cases is more challenging since the data may not ideal. In example, the data losses, communication losses and missing information might occur. Furthermore, when the power system grows, the ANN model should be reformulated.

Conclusions

The proposed method model is built based on the ANN which has seven hidden layers for the instantaneous voltage magnitude. The proposed method can detect voltage stability status and critical bus's location with high accuracy without requiring the complete model of power systems. From the simulation result, the best accuracy can be obtained by the 14 PMUs measurement which has the accuracy > 97% for voltage stability detection and > 96% for critical bus detection. Those results show that for modified IEEE 14 bus test system, the proposed model can represent the complete power system model with the given historical data. The proposed model can consider line contingency condition, loading scenario and load scaling condition so that system variation can also be represented. Integrating the PV as the renewable energy almost has no effect in the accuracy. Moreover, the PMU number and location will affect the accuracy of the critical bus detection. If the credible contingency are specific for a power system, it is not required to install all PMU in each bus. Furthermore, the model can be applied in real time prediction since the computational time are still reasonable compared to the classical method which the required computation time is between 16 and 18 s per detection.

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All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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Data availability
Data will be made available on reasonable request to its authors.

Declarations

Competing interests
All authors declare that they have no competing interests.

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