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ORIGINAL PAPER

Machine Learning Techniques Applied to On-Line Voltage Stability Assessment: A Review

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Abstract

Electric power systems have become larger, more complex and found to be operating close to their stability limits with small security margin. In such situation, fast and accurate assessment of voltage stability is necessary in order to prevent large-scale blackouts. Due to its ability to learn off-line and produce accurate results on-line, machine learning (ML) techniques i.e., artificial neural networks, decision trees, support vector machines, fuzzy logic and adaptive neuro-fuzzy inference system are widely applied for on-line voltage stability assessment. This paper focuses on providing a clear review of the latest ML techniques employed in on-line voltage stability assessment. For each technique, a brief description is first presented and then a detailed review of the finding published research papers discussed the application of this technique in on-line voltage stability assessment is presented. Based on the conducted review, some discussions and limitations of ML techniques are finally presented.

1 Introduction

In the last decade, serious power grid blackouts have occurred throughout the world bringing with them important economic losses and affecting the lives of local residents. Voltage instability incidents have been identified as contributing factors in several recent worldwide blackouts such as the large-scale power failure occurred in the Tokyo metropolitan area in 1987 [1]. The blackout incident affected Egypt in April 24, 1990 where 50 million people were affected for 6 h [2]. This blackout was characterized by a fast local voltage collapse, followed by sudden total voltage collapse. Another incident is the blackout affected around 50 million people in eight U.S. states and two Canadian provinces on 14th August 2003. Estimates show that this blackout interrupted around 63 GW of load resulting in an economic loss of approximately 4–6 billion USD. Recently, on 2012 India suffered a severe and large blackout following a voltage collapse due to the overloading of transmission lines. This blackout affected around 670 million people in 22 Indian states [3]. These blackouts have large impacts that are both direct such as the interruption of an activity, function, or service that requires electricity and indirect due to the interrupted activities or services.

Voltage instability phenomenon is generally associated with a gradual or uncontrollable drop in voltage magnitude after disturbances in the system, increase in load demand or incapacity to cover the demand for reactive power. The voltage collapse is the process by which voltage instability leads to loss of voltage in an important part of the system. When the power system is operating with insufficient voltage stability margin in one or more regions, it becomes more likely to voltage collapse. In order to mitigate the risk of voltage collapse, stability analysis should be considered during both planning and real-time operating of power systems. In contrast to the off-line planning, where the computational speed may not be important, in on-line analysis, real-time tools are of great importance for assessing the voltage stability of power system.

In recent years, machine learning (ML) based techniques such as artificial neural networks (ANNs), decision trees (DTs), fuzzy logic (FL), adaptive neuro-fuzzy inference system (ANFIS) and support vector machines (SVMs) have attracted the researchers' attention due to their ability to solve nonlinear problems with desired speed and accuracy. The present paper mainly focuses on providing a clear review of the latest ML techniques used in on-line voltage stability assessment. This review is organized as follows: Sect. 2 gives a brief description of voltage stability

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phenomenon. Section 3 first briefly explains each ML technique and afterward presents a review of the finding published works discussed the implementation of this technique in on-line voltage stability assessment. Section 4 presents some discussions and limitations of ML techniques. Finely a conclusion is drawn in Sect. 5.

2 Voltage Stability

2.1 Definition and Classification

According to the IEEE/CIGRE joint task force on stability terms and definitions [4], voltage stability refers to the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance from a given initial operating condition. The main factor causing voltage instability is the inability of the power system to meet the demand in heavily stressed systems. Other factors contributing to voltage stability are the generator reactive power limits, outage of any equipment (transmission lines, generators or transformers), load characteristics, characteristics of reactive compensation devices and the action of voltage control devices [5].

Voltage stability is classified into short-term voltage stability and long-term voltage stability. The short-term voltage stability involves dynamics of fast acting load components such as induction motors, electronically controlled loads and HVDC converters. The study period of interest is in the order of several seconds and analysis requires solution of suitable system differential equations. The long-term voltage stability involves slower acting equipment such as tap-changing transformers, thermostatically controlled loads, and generator current limiters. The study period of interest may extend to several or many minutes, and long-term simulations are required for analysis of system dynamic performance [4]. In addition to this classification, the voltage stability can be fast (short-term voltage stability) or slow (long-term voltage stability) as demonstrated in Fig. 1.

2.2 Concepts Related to Voltage Stability

2.2.1 Voltage Collapse

The static voltage stability problem becomes a serious type of voltage instability which is associated with the increased loading of the power system and the inability to meet the demand for real or reactive powers. It is characterized by an initial progressive decrease of voltage magnitude and a final rapid decline. Figure 2 depicts the relationship between the load bus voltage and the active power transfer through the transmission line, denoted as a P–V curve. As the loading increases, the voltage at the load bus decreases. The edge of the curve is the maximum active power (P_{max}) that can be transmitted over the transmission line and it considered as the "voltage collapse point". Consequently, the voltage collapse can be defined as "the process by which voltage

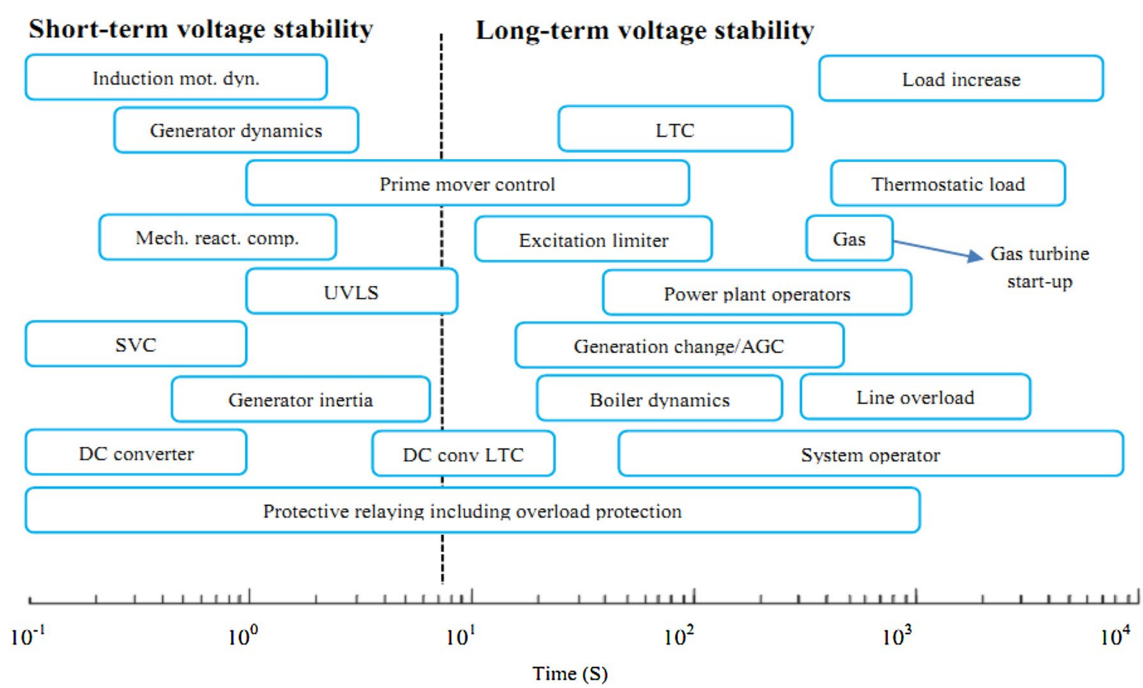

Fig. 1 Different time responses for voltage stability phenomena [5]

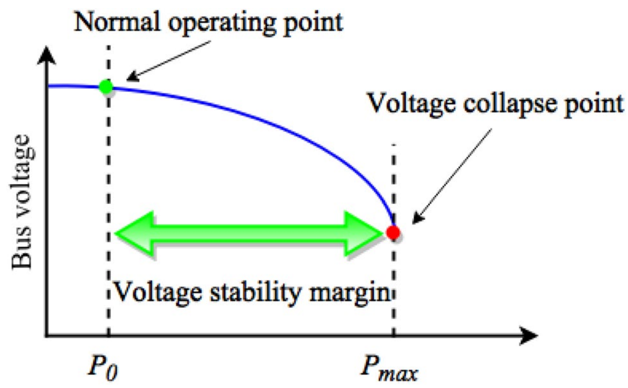

Fig. 2 *P–V* curve for the simple two-bus system

instability causes the loss of voltage in an important part of the system".

2.2.2 Voltage Stability Margin

One of the most frequent terms related to the voltage instability is the voltage stability margin (VSM) which corresponds to a measure of the distance from the current operating point to the critical point (See Fig. 2). Under some specific conditions, this critical point corresponds to the maximum loading point or the saddle-node bifurcation point at which voltage collapse occurs [6].

2.2.3 Loadability Margin

Loadability margin can be directly obtained from the *P–V* curve as illustrated in Fig. 2. The normal operating value of active power, delivered to the load, is P_0 and the maximum possible power transfer is P_{max}. The loadability margin is defined as the difference between these two quantities.

2.2.4 Voltage Security

Voltage security is the ability of the power system, not only to operate stably, but also to remain stable (as far as the maintenance of system voltage is concerned) following any reasonably credible contingency or adverse system change [7].

2.2.5 Voltage Stability Assessment

The voltage stability assessment (VSA) or monitoring involves the determination of how close the system is to voltage instability. This assessment identifies whether the current operating point is secure or not.

2.3 Voltage Stability Assessment Tools

Voltage stability assessment is one of the important parts of the planning and operating of power systems. Voltage stability assessment methods are categorized into off-line and on-line studies. The first category is conducted in the power system planning and the second category is conducted during the system operation. The on-line assessment is to justify whether the current operating point is secure or insecure, and to determine how close the system is to voltage collapse point which is called the VSM.

Many different methods have been introduced to assess the voltage stability and to find the VSM among them:

2.3.1 Methods Based on Modal Analysis

The modal analysis method proposed by Gao et al. [8] on 1992 depends on the power flow Jacobian matrix and it can predict the voltage collapse in complex power systems. This method involves the computation of the smallest eigenvalues and associated eigenvectors of the reduced Jacobian matrix obtained from the load flow solution. The eigenvalues are associated with a mode of voltage and reactive power variation which can give a relative indication of how close the system is to the voltage collapse.

2.3.2 Methods Based on Energy Function

The energy function method has been initially applied to determine the transient stability of one machine-infinite bus system or two-machine system based on the equal area criterion. Albeit that the energy function method is more appropriate for transient stability assessment, many authors have associated this technique with measure voltage stability margin in the static cases. The first application of energy function for voltage collapse analysis was performed by DeMarco and Overbye [9]. The energy function technique is, also, used to rank the system buses according to their participation in voltage collapse [10].

2.3.3 Methods Based on Loading Margin

One of the important tools to assess voltage stability is the methods based on loadability margins. This loadability margin can be computed by *P–V* and *Q–V* curves, continuation power flow (CPF) method or by using voltage stability indices.

- *P–V* and *Q–V* curves
  The *P–V* and *Q–V* curves are the most used methods to evaluate the voltage stability [11]. They are used to determine the VSM of the power system. The *P–V* curve can be obtained by gradually increasing the active power,

by constant power factor, at load bus or area and executing consecutive power flow equations. An example of such curves is the Fig. 2 which depicted the relationship between the load bus voltage and the active power transfer through a transmission line. The edge point or voltage stability collapse point is the point where the power flow process will diverge due to the singularity of the Jacobian matrix. The distance between the voltage collapse point and the normal operating point or the so-called VSM is used as the voltage stability criterion. In the same manner, the *Q*–*V* curves are used to indicate the sensitivity and variation of bus voltage magnitude with respect to reactive power injections and absorptions. The *Q*–*V* curve can be used as voltage stability assessment tools, taking the edge point of the curve as the collapse point and the MVar distance between this point and the normal operating point as the reactive power margin [11].

- Continuation power flow (CPF)
  CPF is an iterative process that finds a gradation of power flow solutions at different operating points by using branch tracing methods or also called predictor–corrector methods. CPF is utilized to determine the steady-state voltage stability limits. These limits are determined by drawing the nose curve where the nose represents the maximum power that can be transmitted over the transmission line. The nose curve can be drawn by the variation of load voltage magnitude with the automatic changes of the loading parameter. From a known base solution, a tangent predictor is used so as to estimate next solution for a specified pattern of load increase. Then, the corrector step determines the exact solution using Newton–Raphson technique. After that, a new prediction technique is made for a specified increase in load based upon the new tangent vector. Then corrector step is applied. This process goes until a critical point is touched [12].
- Voltage stability indices (VSIs)
  The methods based on voltage stability indices are very popular due to the uncomplicated interpretation of the index used. Many indices have been proposed in the literature to assess the voltage stability of power systems and to find the VSM. These indices can be classified into bus, line and overall VSIs. The line VSIs (e.g. Fast voltage stability index (FVSI), line stability index (L_{mn}), line stability factor (LQP), line stability index (L_p), voltage collapse proximity index (VCPI), line collapse proximity index (LCPI)) are used to assess the voltage stability of the transmission lines. Bus VSIs (e.g. L-index, voltage stability index (VSI_{bus}), simplified voltage stability index (SVSI), S difference criterion (SDC)) compute the voltage stability of system buses and the last type which is the overall VSIs (e.g. Network sensitivity approach (SG)) are not related to the system busess and lines. This type can only predict the voltage collapse point of the power system [13, 14].

3 Voltage Stability Assessment Using ML Techniques

As abovementioned, there are numerous tools that have been developed to conduct a comprehensive analysis of the voltage stability assessment, such as *P*–*V* and *Q*–*V* curves, CPF and voltage stability indices. However, the developed software tools have the scarcity to be used in a real-time or online operation as they are computationally time-consuming due to its reliant on a complex mathematical modelling of a power system. The aforementioned predicament of enormous computational requirements could be resolved by utilizing the ML techniques. The ML includes many techniques such as artificial neural networks (ANNs), decision trees (DTs), fuzzy logic (FL), adaptive neuro-fuzzy inference system (ANFIS) and support vector machines (SVMs). In this paper, we will refer only to the ML techniques that have been applied widely in the literature for the case study of on-line power system voltage stability assessment.

3.1 Artificial Neural Networks (ANNs)

A neural network is a computational model proposed in the late 1940s by Hebb [15]. It was inspired by the operations of biological neural systems. In 1954, Farley and Clark [16] first employed computational machines to simulate a Hebbian network at Massachusetts Institute of Technology (MIT) and then called calculators. Rosenblatt [17] developed the perceptron in 1958, and in 1975 the back-propagation algorithm was introduced by Werbos and Beyond [18]. In 1982 and 1984, the Hopfield and the Kohonen neural networks were provided by Hopfield [19] and Kohonen [20]. In 1986 [21], Rumelhart and McClelland introduced the back-propagation learning algorithm. In 1987, several research programs based on ANNs were initiated and the list of their application has been extended to large practical tasks [22]. Between 2009 and 2012, the recurrent and the deep feed-forward ANNs were developed in the research group of Jurgen Schmidhuber at the Swiss AI Lab [23].

Several ANN architectures and various neural network combinations have been proposed in the literature for on-line voltage stability assessment. multi-layered perceptron (MLP) neural network trained by the back-propagation algorithm is firstly introduced in [10, 24, 25] for computing the VSM using energy method. An extended work on the MLP has been employed to assess the voltage stability for a dynamic power system model [26, 27]. Further improvement of MLP performance in on-line monitoring of voltage stability could be realized by reducing the input data at an optimal size [28]. In the same context, Ying et al. [29] proposed the use of hybrid MLP networks and ward equivalent approach network reduction. The proposed approach possesses the properties of ward equivalent method to update the parameters of the equivalent model for representing real-time topology change of the power system. In tandem with the input data minimization, this can also be perpetrated by using several feature extraction methods such as the principal component analysis that augment the performance of MLP to assess the voltage stability in an on-line manner [30, 31]. In [32], a systematic way to train separate MLP network for various contingencies is presented. In this work, the load active and reactive powers are used as the input features for the MLP. In [33], an MLP based input features selection using mutual information method is proposed to estimate the voltage stability level at various load conditions and contingencies. Joya et al. [34] used a sequential learning strategy to design a single feed-forward back-propagation network to estimate the line voltage stability index for different load conditions. In [35], a regression-based method of selecting features for training a separate ANNs is proposed to assess the voltage stability considering deferent contingencies. Debbie et al. [36] proposed an ANN-based method to estimate the VSM of power system under normal operating conditions as well as under N-1 contingencies. Venkatesan and Jolad [37] proposed the application of MLP based approach for fast voltage contingency ranking. In the proposed approach, the off-line load flow studies are adopted to find the minimum singular value (MSV) and the results from load flow study are used to train the MLP network to estimate the MSV. Authors in [38] developed a new extreme learning machine model for precise and fast prediction of voltage stability under different loading conditions and under contingencies. Authors in [39] proposed a new MLP network-based algorithm that requires only a minimum number of inputs to estimate the voltage magnitude of each critical bus in a power system under normal and contingency states. Another approach to find the fewest input variables required to approximate the VSM with sufficient accuracy and high execution speed is proposed in [40]. In [41], a Z-score based bad data processing algorithm is implemented to enhance the estimation accuracy of the feed-forward ANNs. In [42], three ANN types i.e., MLP, RBF and layer recurrent (LR) have been used to assess the voltage stability of the power system in on-line manner. According to the obtained results, the RBF shows superior prediction ability of fast voltage stability index (FVSI) compared to the MLP and LR methods.

The application of radial basis function (RBF) neural network for on-line voltage stability assessment has also been performed by several researchers. Jain et al. [43] applied both supervised and unsupervised learning to RBF network in order to reduce the number of neural networks required for voltage contingency screening and ranking. Sahari et al. [44] used the active and reactive loads on all load buses as input set of RBF network for on-line monitoring of voltage stability. Authors in [45] proposed the application of RBF network-based energy method for on-line estimation of VSM. Arya et al. [46] proposed the use of RBF network to get the probabilistic risk of voltage collapse for various operating conditions. In this work, the training and testing instances have been generated using Monte-Carlo simulation. RBF neural network is also applied by Moradzadeh et al. [47] to predict the static voltage stability index and to rank the critical line outage contingencies. In this study, three distinct feature extraction algorithms are used to speed-up the training process via reducing the input training vectors dimensions. In [48], several dimensionality reduction techniques are employed to enhance the predictive ability of the RBF network in the estimation of the voltage stability level. In [49], a comparison between ANNs trained using linear basis function and RBF in the estimation of line voltage stability index (L_{mn}) has been presented. The results show that both the ANNs paradigms are suitable for L_{mn} index prediction. In [50] the RBF network is adapted to estimate the VSM using the dominant extracted features of the voltage profile by multi-resolution wavelet transform and principal component analysis.

The application of self-organizing Kohonen-neural network (SKNN) for fast indication and visualization of voltage stability has been discussed in [51]. In [52], a new ANN architecture called the parallel self-organizing hierarchical neural network (SHNN) is proposed to estimate the loadability margin with static var compensator. Chen et al. [53] proposed a new approach to compute a risk of low voltage using neural network ensemble (NNE). In this work, the probability model of system contingency and the impact model of low voltage are built, first, and then the corresponding risk index is computed to form the NNE system. Chakraborty et al. [54] incorporated a self-organizing feature map with RBF network for determination and classification of the power system voltage stability level. Notwithstanding the fact that the ANN has gained attention from researchers as a tool for on-line voltage stability assessment, it has some drawbacks. Duraipandy and Devaraj [38] proposed the use of Extreme Learning Machine (ELM) technique for on-line assessment of voltage stability for multiple contingencies. A single ELM model has been developed for credible contingencies for accurate and fast estimation of the voltage stability at different loading conditions. In [55], the same authors proposed a new index based on ELM. The proposed index takes real and reactive power load as input parameters and a voltage stability margin called ELM-VSI as output.

3.2 Decision Tree (DT)

DT, also named classification and regression tree, is a decision support tool which uses a binary tree-like graph or model for representation of possible solutions to a decision based on certain conditions. It was first developed by Breiman et al. [56] in the 1980s and was firstly introduced into the field of power systems by Wehenkel et al. [57] in 1989. Among the many other applications of DT in power systems, security assessment is the most versatile [58, 59]. DT is adopted to assess the voltage security of the American Electric Power (AEP) system [60, 61]. Recently, DT has been applied in on-line voltage stability assessment with wide-area measurements system [62–64]. Zheng et al. [62] proposed the use of DT for fast evaluation of power system oscillatory stability and voltage stability based on voltage and current phasor measurements. Li and Wu [63] used the voltage phase angle difference that obtained by PMUs in order to improve DT's identification accuracy. Beiraghi and Ranjbar [64] developed a new on-line voltage security assessment method based on wide-area measurements and decision-tree algorithm. In the developed method, the adaptive boosting (AdaBoost) techniques are employed to generate a combined model which is used to predict the voltage security of the power system using continuous wide-area measurements. Krishnan and McCalley [65] proposed a process of deriving DT for power system security assessment of multiple contingencies based on a novel contingency grouping method. The contingency grouping is based on newly devised metric called progressive entropy, which is graphical metric that finds the overlap of class boundary progression of various contingency's training databases. The proposed method was illustrated on the Brittany region of French power system to derive decision rules for five critical contingencies against voltage stability problems.

DT has been also combined with other algorithms, such as principal component analysis and fuzzy logic, for on-line voltage stability monitoring. Mohammadi and Dehghani [66] developed a combined method for on-line voltage security assessment in which the dimension of the token data from PMUs is reduced by principal component analysis (PCA). In [67], the DT-based PCA method is combined with two optimization algorithms namely biogeography-based optimization and invasive weed optimization to assess the voltage stability of the power system. In the proposed method, the training data are reduced first using PCA, afterwards the two optimization algorithms are used to find the optimum dimensions of the PMU data and to minimize the misclassification rate of the security test. Abidin and Hussein [68] proposed a new approach based on fuzzy decision trees (FDTs) to assess the voltage security of power system. The objective of the proposed FDTs is to analyses power system parameters and locates probable locations that could contribute to voltage collapse. The same authors improved the previous method in [69] by adding more contributing attributes onto the existing FDTs. The authors compared these results with those obtained in [70] and concluded that the adding of other contributing attribute values into the basic FDTs sequence will improve the FDTs in terms of its performance and accuracy.

3.3 Fuzzy Logic (FL)

Fuzzy logic is an extension of Boolean logic introduced in 1965 by Zadeh [71, 72]. FL can be defined as the nonlinear mapping of an input data set to a scalar output data [73]. FL has been widely applied in almost every part of a power system [74–78]. In the last years, various researchers have applied FL to evaluate the voltage stability state of the power system. Ramaswamy and Nayar [79] proposed an efficient fuzzy based approach to obtain on-line estimates of bus voltages for an outage and/or projected load changes. In this approach, a fuzzy model for each load bus and contingency has been developed and the voltage at any load bus has been independently estimated. The application of extracting rules for voltage security monitoring based on synchronized phasor measurements has been proposed by Liu et al. [80]. In the proposed approach, the two-layer Fuzzy Hyper-rectangular Composite Neural Network is developed and performed on the IEEE 30-bus system under various operating conditions. According to the simulation results, the rule-based approach to voltage security margin estimation opens up new possibilities for power system protection and control. Nageswararao and Jeyasurya [81] proposed a fuzzy based expert system to evaluate the voltage stability of the power system by monitoring the eigenvalues of the load flow Jacobian with the help of modal analysis. Udupa et al. [82] presented a reactive power control approach based on fuzzy sets theory for voltage stability enhancement by monitoring L-index. The performance of the developed fuzzy system is compared with conventional optimization technique and satisfactory results have been obtained. In [83], a novel fuzzy voltage stability index (FVSI) for identifying critical buses, subject to normal and contingency mode of operations, has been introduced. The new proposed index is based on the extinction of fuzzy power flow algorithm to support the continuation technique. The proposed FVSI serves as a good indicator for identification of critical buses both in normal and contingency conditions.

3.4 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) model is first introduced by Jang [84] in 1993. It is based on the combination of the advantages of ANNs capability in learning from processes and fuzzy interpretation of the FL system. In recent years, ANFIS model has emerged as a strong tool for power system applications. It has been applied in different power system areas such as transmission line faults [85], power quality [86], frequency control [87], and power system stability [88–94]. One of the first voltage stability approaches in which Neuro-fuzzy algorithms were applied is reported in [88]. In this work, a novel architecture based on Neuro-fuzzy and voltage, active power and reactive power dimensional surfaces is proposed for predicting power system voltage security indices. The approach was found to be very effective, with the system providing good predictions of voltage collapse under a wide range of scenarios. ANFIS has been also applied to compute the loadability margin of the power systems incorporating STATCOM and SVC [89–91]. In [92], a Fuzzy Inference Engine is developed and optimized by two different approaches (neural networks and genetic algorithms) to evaluate the security margins of power system. The simulation results show that the proposed approaches allow the correct estimation of the voltage security margin with a high level of reliability, accuracy and robustness. In [93], a new method based on ANFIS model and voltage stability indices computed by a voltage stability tool namely VOSTA (voltage stability) has been developed to evaluate the voltage stability of the EHV Italian transmission network. Torres et al. [94] used subtractive clustering (SC) and ANFIS to estimate the loadability margin of power system. This method has proven to give good results to deal with uncertain load behavior and hence, can be implemented in a real-time environment. Amroune et al., [95] proposed the application of ANFIS model in predicting VSM with regards to the input data of voltage magnitudes attained from PMUs.

3.5 Support Vector Machines (SVMs)

SVM [70] is a supervised learning technique with different learning algorithms that are used for developing of classification and regression models. In recent years, SVM is emerged to be an effective computational technique due to their many advantages and has already been applied to different engineering areas, except in power system stability monitoring where its application is still very limited. Cortés-Carmona et al. [96] employed the SVM based Bayesian rule to classify the status of power system either it is secure, alert and emergency. This approach has been applied relatively analogous to the proposed multi-class SVM used for security assessment as highlighted in [97]. In the proposed approach, four different statuses of system security namely normal, alert, emergency_1 and emergency_2 are considered. Further amelioration of multi-class SVM has been undertaken by consolidating the pattern recognition approach for security assessment [98, 99].

Support vector regression (SVR), the most common application form of SVM, has also been applied to evaluate the voltage stability of a power grid [100–102]. In [100], the SVR model has been used to assess the voltage stability of power system incorporating flexible alternating current transmission systems (FACTS) devices. In [101], the v-SVR and ε-SVR models with RBF and polynomial kernel functions have been used in on-line prediction of voltage stability margin. Recently, Sajan et al. [102] proposed a hybrid model combining genetic algorithm (GA) with SVR for voltage stability monitoring. It was reported that the proposed GA-SVR model has better performance compared to the MLP neural networks. However, the performance of GA is imperfect, it encloses a sequence of processes i.e., coding, selection, crossover, and mutation, which could affect the speed and the accuracy of the optimization. Another problem is related to the difficulty of choosing of GA operators such as population size, selection method, crossover rate and mutation rate, which have a significant impact on the convergence to the optimum solution. In [95, 103], tow powerful nature-inspired algorithms namely, ant lion optimization (ALO) algorithm and dragonfly algorithm (DA) were employed to determine the optimal parameters of SVR model. The obtained results suggested that the two models (i.e., ALO-SVR and DA-SVR) can be successfully applied to predict the voltage stability margin of power system. Yang et al. [104] proposed a new synchrophasor measurements-based voltage stability estimation method using least-square SVM with on-line learning. The proposed method is tested on the New England 39-bus system and the obtained results confirmed the effectiveness of this method in on-line voltage stability assessment.

4 Discussions and Limitations of ML Techniques

The research in on-line power system voltage stability assessment based on ML techniques has attracted a number of researchers due to the ability of these techniques to

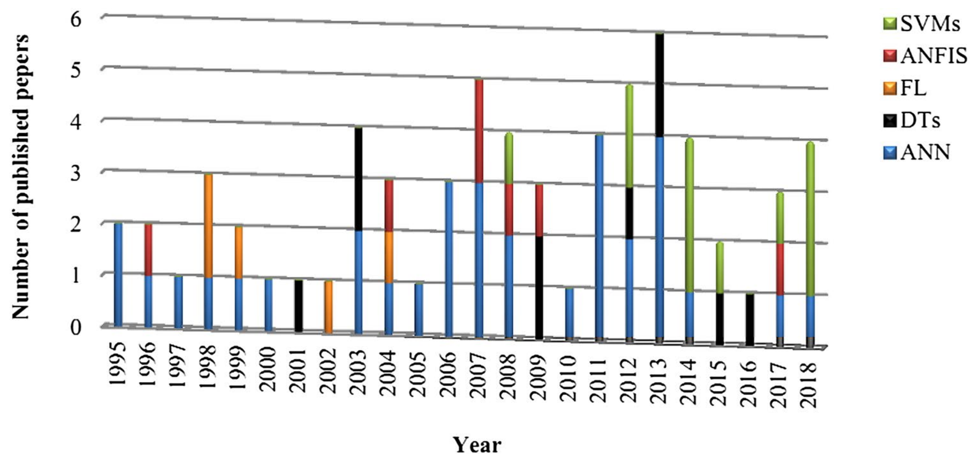

Fig. 3 Overview of number of publications on voltage stability assessment using ML techniques by year

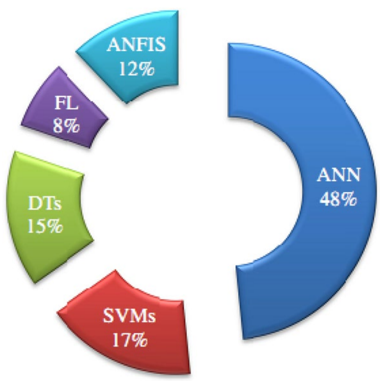

Fig. 4 Overview of ML techniques used in on-line voltage stability assessment

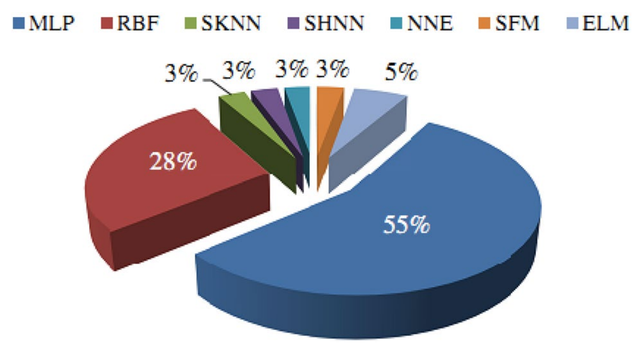

Fig. 5 ANN types used in on-line voltage stability assessment

provide fast and accurate assessment of voltage stability to obviate power system blackouts.

In this paper, the previous research works on on-line voltage stability assessment using ML approaches, published along the past 24 years, are studied. These works were published between 1995 and 2018. An overview of the number of publications by year is given in Fig. 3. This figure shows that there is a continuous research interest on the on-line voltage stability assessment using ML techniques. Between the years 1995 and 2000 researchers mainly focused on the application of ANN and from 2008 their focus was widened on other techniques. As can be seen from Fig. 4, over half of papers (48%) utilize ANN based approach. ANNs have the ability to identify and classify complex relationships which are nonlinear and result from large mathematical models. The main advantage of the ANN is the ability to reach complicated input–output mappings through a learning process without explicit programming and complex modeling. Thus, ANNs have the potential to play an important role in energy management systems to provide system operators with a fast and reliable indication of voltage instability. A major limitation of the use of ANNs for on-line voltage stability assessment arises due to the fact that the functional relationship itself gets changed from one topology to the other which results in the requirement of an additional ANN for each new topology [38]. Another drawback appears in large-scale power systems, in this case the ANN requires a large input training vectors and this leads to a low speed training process. Figure 5 shows the Types of ANN algorithms used in on-line voltage stability assessment.

SVM is a powerful and promising data classification and function estimation tool that attracted much attention in recent years. Its application in on-line voltage stability assessment is started in 2008 and attained 17% of the published papers as shown in Figs. 3 and 4. According to the reviewed papers the SVM model gives a better performance in terms of accuracy, speed and distribution of high-risk cases compared to the ANN and ANFIS [71, 93, 101]. However, the performance of the SVM model is extremely dependent upon the selection of its parameters [93, 100, 101]. Therefore, the selection of the optimal parameters is of great importance to obtain a good performance of the SVR model. On the other hand, the SVM learning algorithms suffer from exceeding time and memory requirements, if the training pattern set is very large [70].

As shown in Fig. 4, 14% of reviewed papers use DTs method. On-line voltage stability assessment based on DTs system has also its advantages and drawbacks. DTs are of interest because they are more understandable by users for their simpler rules [95]. The problem of using DTs for voltage stability assessment from substation field measurements has not yet been fully explored. It is also imperative to develop a systematic approach to generate a sufficient and realistic knowledge base for off-line training of DTs [66].

The FL and ANFIS based techniques are used for various power system problems, however, its application in on-line voltage stability assessment remained very modest (see Figs. 3 and 4). The main advantage of FL system is its ability to compute with words than numbers (Uses linguistic variables), thus, the exploitation of the tolerance for imprecision and thereby lowers the cost of solution [70]. Though FL is able to translate the expert knowledge into a mathematical framework, there is no systematic method to determine a reliable fuzzy rules and membership functions, especially for large-scale power systems. Another drawback of FL system being in rules robustness i.e., fuzzy rules generated for one system may not work well for other systems. The ANFIS is a well-developed fuzzy inference system that takes advantages of fuzzy logic and neural network. The complexity of internal parameters selection and the high computational costs are the main disadvantages of this technique [101].

An overview of the reviewed papers collected from various online databases, journals and conference proceedings is summarized in the Table 1. Columns 1 and 2 of this Table contain the reference number and the method used. Columns 3 and 4 contain the input and the output of each ML technique. Column 5 contains the system used to test the proposed approach. It can be noted from Table 1 that the implemented techniques use six basic inputs: voltage (magnitudes and phases), load real and reactive powers, generators real and reactive powers, PMU measurements, real power flows and power injections at load buses. Table 1 shows also that studies often employ loadability margin and voltage stability indices as the output of ML techniques. Loadability margin and voltage stability indices are simple, require less computation efforts and are suitable for on-line applications. On the other hand, some studies proposed the use of the stat of the system (secure or insecure) as the indicator of voltage stability. However, this kind of indicators cannot provide enough details about how the systems are near to their stability limits. As another type of inputs or voltage stability indicators, [24, 31] used energy margin, [37] used minimum singular value and [104] used the induction motor slip. But in contrast to voltage stability indices these indicators cannot accurately estimate the voltage stability margin and their computational complexity is very high.

5 Conclusion

Voltage instability phenomenon is considered the main threat to stability, security and reliability in modern power systems. Due to the load changes and sudden contingencies occurrence, off-line voltage stability monitoring can no longer ensure a secure operation of the power system. Hence, fast and efficient methods to assess power system voltage stability are of great importance to experts and industrials in order to avoid a risk of large blackouts. In this paper, a review of the major research works applying ML techniques in on-line voltage stability monitoring has been presented. Firstly, a brief description of each ML technique is reported and then a detailed review of the previous studies discussing the application of this technique in on-line voltage stability assessment has been presented. Finally, a comparative study of these techniques has been performed. It can be concluded that the implementation of ML techniques in on-line voltage stability assessment can enhance the power systems stability, thus, reduce the possibility of blackouts. However, further improvements are still needed to make these techniques compatible with on-line applications.

Compliance with Ethical Standard

Conflict of interest The author declare that he has no conflict of interest.

Appendix

See Table 1

Table 1 Summary of literature review of on-line voltage stability monitoring using ML techniques

Ref. No.	Method used	Input (s)	Output (s)	Test system used
[24]	Multi-layer perceptron network	Voltages, real and reactive power at each bus	Energy measure	IEEE 5-bus
[25]	Multi-layer perceptron network	Active and reactive powers at all buses, generators real and reactive powers	Voltage stability margin	IEEE 5, 14, 30, 57, 118-bus
[26]	Multi-layer perceptron network	Load active and reactive powers, voltage magnitude	J_{LC} index	New England 39-bus
[27]	Multi-layer perceptron network	Active power, reactive power and voltage magnitudes at the load and generating buses	System power margin (M_L), bus power margins (M_j)	IEEE 118-bus
[28]	Multi-layer perceptron network	Injected active and reactive powers in all buses	Voltage phase angles, voltage magnitudes, active and reactive powers of all nodes	92-bus
[29]	Multi-layer perceptron network	Transmission capacity	Voltage Stability Margin	IEEE 118-bus
[30]	Multi-layer perceptron network	Active and reactive powers of the boundary buses	Voltage magnitudes and phase angles of the boundary buses	New England 39-bus
[31]	Multi-layer perceptron network	Active power, reactive power and voltage magnitudes at the load buses	Energy margin	IEEE 24-bus Reliability test system
[32]	Multi-layer perceptron network	Active and reactive line flows	Active power margin	New England 39-bus
[33]	Multi-layer perceptron network	Pre-contingency line flow	L-index	IEEE 30-bus
[34]	Multi-layer perceptron network	Load variation	L_{mn} index	IEEE 14, 30-bus
[35]	Multi-layer perceptron network	Load active and reactive powers	MW margins	New England 39-bus
[36]	Multi-layer perceptron network	PMU measurements	P margin	New England 39-bus
[37]	Multi-layer perceptron network	Voltage magnitudes at all buses, load active and reactive powers, line configuration	minimum singular value	New England 39-bus
[38]	Multi-layer perceptron network	Voltage magnitudes and phase angles at the load buses	Loading margin	IEEE 30-bus
[39]	Multi-layer perceptron network	Load active and reactive powers at vulnerable buses, net active and reactive powers at vulnerable buses	Voltage magnitudes of vulnerable buses	IEEE 14, 30, 57-bus
[40]	Multi-layer perceptron network	Inputs extracted by the Gram–Schmidt orthogonallization procedure	Voltage stability margin	New England 39-bus, Australian power system
[41]	Multi-layer perceptron network and Ward reduction	Complex voltage measured by PMUs	System loadability limit	IEEE 14-bus, 118-bus
[42]	Multi-layer perceptron network, radial basis function network and layer recurrent.	Real and reactive powers at all buses	Fast voltage stability index (FVSI)	IEEE 14-bus, 30-bus
[43]	Radial basis function network	Real and reactive loads at different buses	Voltage performance index	IEEE 30-bus system, a practical 75-bus Indian system
[44]	Radial basis function network	Active and reactive powers on all load buses	L-index	IEEE 6-bus
[45]	Radial basis function network	Load active and reactive powers, generators reactive power. The inputs are identified based on sensitivity analysis	Voltage stability margin	IEEE 118-bus

Table 1 (continued)

Ref. No.	Method used	Input (s)	Output (s)	Test system used
[46]	Radial basis function network	Voltage magnitudes at all buses, load active power	Probability of voltage collapse	6-bus, 25-bus
[47]	Radial basis function network	Active and reactive powers on all load buses	Minimum singular value (MSV), right singular vector (RSV)	IEEE 30-bus
[48]	Radial basis function network	Load active and reactive powers, voltage magnitude, voltage phase	L-index	IEEE 30-bus, 76-bus practical Indian system
[49]	Multi-layer perceptron network and radial basis function network	Active and reactive powers at all load buses	L_{mn} index	IEEE 24-bus reliability test system
[50]	Radial basis function network	Dominant extracted features by wavelet transform	Voltage stability margin	New England 39-bus
[51]	Self-organizing Kohonen-neural network	Generators active and reactive powers, transformer taps	Minimum singular value	Real 500 kV transmission system
[52]	Self-organizing, hierarchical neural network	Active and reactive power injections, firing angle of SVC and bus voltage at which SVC is connected	Voltage stability margin	IEEE 30, 118-bus
[53]	Neural network ensemble	Voltage magnitudes at all buses	Low voltage risk index	New England 39-bus
[54]	Self-organizing feature map and radial basis function network	Load bus voltage, reactive power generation and reactive power loss	Linear voltage stability index (LVSI)	West Bengal state electricity board's (203-bus)
[38]	Extreme learning machine	Voltage magnitudes and phase angles at the load buses	Loading margin	IEEE 30-bus
[55]	Extreme learning machine	Active and reactive powers on all load buses	ELM-VSI	IEEE 30, 118-bus
[60]	Decision trees	PMU-related system parameters.	Stat of the system (secure or insecure).	American electric power system
[61]	Decision trees	Generator vars and angular difference Attributes	Stat of the system (secure or insecure).	American electric power system
[62]	Decision trees	Voltage and current phasor measurements	Stat of the system (stable, alert, unstable)	9-bus, New England 39-bus
[63]	Decision trees	Active power flows and PMU-based voltage angle differences	Stat of the system (secure or insecure)	Zhejiang power grid of China
[64]	Decision trees based bagging and adaptive boosting methods	Active load and active generation variation	Stat of the system (secure or insecure).	IEEE 118-bus
[65]	Decision trees	Total load, bus voltages	Stat of the system (secure or insecure).	French EHV system
[66]	Principal component analysis and decision trees.	Load flow convergence, loading index (LI) and profile index (PI)	Stat of the system (more secure, less secure,…)	New England 39-bus and a part of Iran power grid
[67]	Principal component analysis and decision trees.	PMU data	Power system state (secure or insecure)	66-bus and Iranian power grid
[68]	Fuzzy decision trees	Bus voltage magnitudes	Partitioning system parameters into strong and weak bus components	IEEE 300-bus
[69]	Fuzzy decision trees	Bus voltage magnitudes	Partitioning system parameters into strong and weak bus components	IEEE 300-bus
[79]	Fuzzy logic system	Real and reactive load power, total real and reactive load power	Voltage magnitude at load buses	IEEE 14-bus

Table 1 (continued)

Ref. No.	Method used	Input (s)	Output (s)	Test system used
[80]	Fuzzy hyper-rectangular composite neural networks	Voltage magnitudes and phase angles of PMUs buses	Stat of the system (very secure, secure, alert, …)	IEEE 30-bus
[81]	Fuzzy based expert system	Load bus voltage, generator MVAR reserve	Degree of voltage stability (very stable, stable, …)	New England 39-bus
[82]	Fuzzy logic system	L-index, sensitivity of the L-index, margin of the control variables	New setting of control variables (OLTC tap position, generator excitation setting and size of SVC setting)	IEEE 30-bus, 82 bus Indian power system
[83]	Fuzzy logic system	Voltages at the PV buses, loads and generations	Fuzzy voltage stability index	IEEE 14-bus, 30-bus, and 57-bus
[88]	Adaptive neuro-fuzzy inference system	Active load, active generation	Active and reactive power load, voltage magnitudes	2 machines system, 25 machines system
[89]	Adaptive neuro-fuzzy inference system	Real and reactive loads selected by Kohonen self-organizing map	Load-ability margin	IEEE 30-bus, IEEE 118-bus
[90]	Adaptive neuro-fuzzy inference system	Real and reactive loads selected by Kohonen self-organizing map	Load-ability margin	IEEE 30-bus, IEEE 118-bus
[92]	Adaptive neuro-fuzzy inference system.	Voltages, real injections, number of PV buses, area real and reactive power margins and real losses	Sensitivity of the reactive power production of all generators, the maximum singular value of the inverse of the PF Jacobian and the (N-1) index.	Italian (400/220 kV) transmission network connected to an equivalent of the UCTE network.
[93]	Adaptive neuro-fuzzy inference system.	Stability indices calculated by the VOSTA (VOltage STAbility) tool	Load-ability margin	Italian (400/220 kV) transmission network connected to an equivalent of the UCTE network.
[94]	Adaptive neuro-fuzzy inference system.	Voltage stability indices selected heuristically	Load-ability margin.	IEEE 30, 118, and 300 bus.
[95]	Adaptive neuro-fuzzy inference system	PMU measurements.	Voltage stability index	IEEE 30-bus, IEEE 118-bus
[96]	Support vector machine	Voltage at all buses, generators active and reactive powers	Stat of the system (Normal, Alert, …)	IEEE-RTS of 24 bus
[97]	Multi-class support vector machine	Determined by fisher criteria feature selection	Stat of the system (Normal, Alert, …)	New England 39-bus
[98]	Support vector machine	PMU measurements	Power system state (Secure or insecure)	New England 39-bus
[99]	Support vector machine based binary classification	Determined by sequential forward selection method	Stat of the system (Normal, Alert, …)	New England 39-bus, IEEE 57-bus
[100]	Artificial imine system-support vector machine	Real and reactive power load	Loadability margin index	IEEE 30-bus, Indian 181-bus
[101]	Support vector regression	Real and reactive power load	Loadability margin index	IEEE 30-bus, IEEE 118-bus
[102]	GA optimized support vector regression.	PMU measurements	Loadability margin index	IEEE 30-bus, IEEE 118-bus
[103]	DA optimized support vector regression.	PMU measurements	Voltage stability index	IEEE 30-bus, Algerian 59-bus
[104]	Least square support vector machine with online learning	PMU measurements	Induction motor slip	New England 39-bus

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