Support Vector Machine for Transient Stability Assessment: A Review

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***Abstract*—Accurate transient stability assessment is a crucial prerequisite for proper power system operation and planning with various operational constraints. Transient stability assessment of modern power systems is becoming incredibly challenging due to rising uncertainty and continuous integration of renewable energy generation. The stringent requirements of exceedingly high accuracy and fast computation speed has further necessitated accurate transient stability assessment for power system planning and operation. The traditional approaches are unable to fulfil these requirements due to their shortcomings. In this regard, the popularity of prospective approaches based on big data and machine learning, such as support vector machines, is constantly on the rise as they have all the features required to fulfil important criteria for real-time TSA. Therefore, this paper aims to review the application of support vector machine for transient stability assessment of power systems. It is believed that this work will provide a solid foundation for researchers in the domain of machine learning and computational intelligence-based applications to power system stability and operation.**

Keywords—computational intelligence, machine learning, power system, support vector machine, transient stability

I. Introduction

The growing load demand in power systems without accompanying investments in generation and transmission has impacted the evaluation of transient stability, demanding more reliable and faster tools. One of the most intriguing challenges in online operation of power systems is the evaluation of transient stability. Its significance has intensified due to the reduction of operational safety margins, increasing renewable generation and the introduction of competitive electricity market. Conventional analytical techniques such as time domain simulation and direct approaches do not allow to take preventive or corrective actions in appropriate time.

The most common and simplest approach to compute the transient stability status of a power system is the time-domain simulation of the nonlinear differential equations which govern the power system [1]. This approach requires accurate information on the system topology during and after the disturbance and thereby, it is time consuming. Another method for determining the stability after a contingency is the Transient Energy Function (TEF) approaches based on Lyapunov stability or Energy Function theory [2]. In this technique, the stability assessment is performed by comparing the difference between the kinetic energy and potential energy against a reference value for a specific fault. However, there are obstacles in computing the levels of kinetic and potential Energy under particular disturbances for large scale power systems [2]. The Equal Area Criterion (EAC) approach is based on the same theory and offers a way to evaluate the transient stability of a multimachine system represented as a one machine connected to an infinite bus system without solving the cumbersome system of differential-algebraic equations. Although EAC is powerful graphic approach, it involves obtaining an equivalent machine and allows only the classical generator model that represents only the generator's mechanical dynamics [3]. The Extended Equal Area Criterion (EEAC) is a fusion of the time-domain simulation and energy functions [4]. Although, this approach is computationally more efficient, but less accurate than time-domain simulation. A potential solution to conquer the flaws of the above-mentioned approaches for transient stability assessment (TSA) is the application of novel soft computing approaches [5].

In recent times, various different Machine Learning (ML) approaches have been proposed for real-time TSA. For instance, Decision Tree (DT) [6- 7] is one of the pragmatic algorithms for predicting power system transient stability. Moreover, ensemble DT (Random Forest) has been considered for transient stability evaluation [8]. Artificial Neural Networks (ANNs) have also been considered to enhance the performance of transient stability status prediction [9- 10]. Support Vector Machine (SVM) is regarded one of the most useful approaches used in real-time TSA [11]. As mentioned there are various ML approaches for TSA; however, this paper specifically focuses on SVM.

The rest of the paper is organized as follows. Section II discusses background and overview of ML. Section III elaborate various steps of ML. Section IV provides background and overview of SVM. Section V provides a summary of various work of SVM application to TSA. Section VI provides research gaps and suggestions for future work. Finally, Section VII concludes the paper.

II. Machine Learning: Background and Overview

ML is broadly regarded as the subset of artificial intelligence [12] (simulation of human intelligence in machines, which are programmed to think like humans and mimic their actions), as outlined by Fig. 1. ML basically is an application of artificial intelligence that provides systems the ability to automatically learn and enhance from experience without being explicitly programmed [12-13]. In fact, the ML performs data analysis, using a set of instructions, through a variety of algorithms, for decision making and/or predictions [14]. Laborious designing and programming of algorithms are essential to be conducted, for ML, to implement diverse functionalities, such as, classification, clustering, and regression. Deep Learning (DL) is a class of ML algorithms that uses multiple layers to progressively extract higher-level features from the raw input. For instance, in image processing, lower layers may identify edges, whereas higher layers may distinguish the concepts relevant to a human being, such as digits, letters or faces [15]. It is majorly used for speech recognition, computer vision (high-level understanding from digital images or videos), medical image analysis, and natural language processing. There are numerous architectures used in DL such as deep neural networks, deep belief networks, recurrent neural networks, long short-term memory, and convolutional neural networks. The DL generally requires huge processing power and massive data [15]. The focus of this work is, however, on ML.

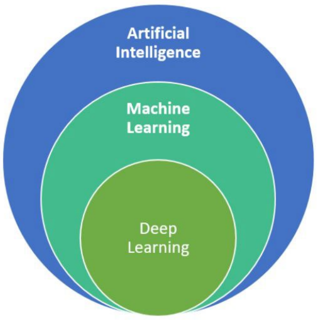

Fig. 1. ML as a subfield of artificial intelligence.

ML differs from traditional programming, in a very distinct manner. In traditional programming, the input data and a well written and tested program is fed into a machine to produce output. When it comes to ML, input data along with the output is fed into the machine during the learning phase, and it works out a program for itself. This is illustrated in Fig. 2 [16].

During the last decade, ML, and DL has demonstrated promising contributions to many research and engineering areas, such as data mining [17], medical imaging [18], communication [19], multimedia [20], geoscience [21], remote sensing classification [22], real-time object tracking [23], computer vision-based fault detection [24], and so forth. The integration of advanced information and communication technologies, specifically Internet of Things (IoT), in the power grid infrastructures, is one of the main steps towards the smart grid. Since the vital capability of IoT devices is their capability to communicate data to other devices in a more pervasive fashion, and hence a massive amount of data is made available at the control centres. Such meaningfully enhanced system condition awareness and data availability necessitates ML-based solutions and tools to conduct efficient data processing and analysis, to encourage the system operational management and decision-making [25]. Therefore, ML has been applied in various fields of power system, such as load forecasting [26], fault diagnosis [27], substation monitoring [28], reactive power control [29], unit commitment [30], maintenance scheduling [31], wind power prediction [32], energy management [33], load restoration [34], solar power prediction [35], state estimation [36], TSA [37], economic dispatch [38], and electricity price forecasting [39].

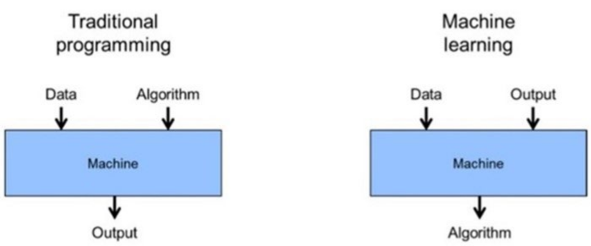

Fig. 2. Traditional programming vs ML.

III. Steps of Machine Learning

There are seven main steps of successfully implementing ML. They are outlined below and illustrated in Fig. 3 [40].

A. Gathering Data

The first and the most significant step of ML is gathering data. This step is very critical, as the quality and quantity of data gathered will directly determine how good the predictive model will turn out to be. The data collected is then tabulated and is commonly called as the training or learning data.

B. Data Preparation

After the training data is gathered, the next step of ML is data preparation, where the data is loaded into a suitable place and then, prepared for use in ML training. Here, the data is first put all together and consequently, the order is randomized as the order of data should not affect what is learned. This is also a good chance to do any visualizations of the data, as this will help see if there are any pertinent relationships between the different variables, and presence of any data imbalances or anomalies. Also, at this stage, the data must be divided into two parts. The first part, which is used in training the model, will be most of the dataset and the second will be used for the evaluation (validation and testing) of the performance of the trained model.

C. Model Selection

The subsequent step that follows in the workflow is choosing a model among the many that researchers and data scientists have created over the years. There are different algorithms for different tasks. Some are appropriate for image data, others for sequences (such as text, or music), some for numerical data, others for text-based data. A selection should be made based on the task required.

D. Training

After the above-mentioned steps are completed, the next step involves training, where the data is used to incrementally improve the ability of the model to predict. The training process requires initializing some random values for the model, predicting the output with those values, then comparing it with the model’s prediction and eventually, adjusting the values such that they match the predictions that were made formerly. This process then replicates, and each cycle of updating is called one training step.

E. Evaluation

Once training is complete, evaluation is performed. This is where the testing dataset comes into play. Evaluation allows the testing of the model against data that has never been seen and used for training and is meant to be illustrative of how the model might perform in the real world.

F. Hyperparameter Tuning

Once the evaluation is over, any further improvement in the training process is possible by tuning the parameters. There were a few parameters that were implicitly assumed when the training was done. Another parameter included is the learning rate that defines how far the line is shifted during each step, based on the information from the previous training step. These values are significant in the accuracy of the training model, and how long the training will take. For complicated models, initial conditions play a significant role in the determination of the outcome of training. Differences can be seen depending on whether a model starts off training with values initialized to zeroes versus some distribution of values. These parameters are commonly referred to as hyperparameters. The tuning of these parameters depends on the dataset, model, and the training process.

G. Prediction

ML is fundamentally using data to answer questions. Prediction is the final step where you get to answer few questions. This is the point where the value of ML is realized. The model gains independence from human interference and thus, draws its own conclusion, based on its data sets and training process. Here, eventually, the trained model can be used to predict the outcome for any desired inputs.

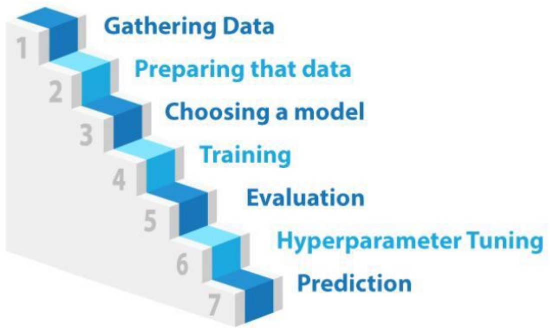

Fig. 3. Seven steps of ML.

IV. SVM: Background and Overview

A SVM is a supervised learning algorithm that can use given data to solve certain problems by attempting to convert them into linearly separable problems [41]. It was first introduced by Vapnik [41-42] and was elaborated by Schölkopf et al. [43]. SVMs find a broad application in classification problems. They distinguish between two classes by finding the optimal hyperplane that maximizes the margin between the closest data points of opposite classes. The number of features in the input data determine if the hyperplane is a line in a two-dimensional space or a plane in a *n*-dimensional space. Since multiple hyperplanes can be found to differentiate classes, maximizing the margin between points enables the algorithm to find the best decision boundary between classes. The lines that are adjacent to the optimal hyperplane are known as support vectors as these vectors run through the data points that determine the maximal margin. The SVM algorithm is widely used in ML as it can handle both linear and nonlinear classification tasks. However, when the data is not linearly separable, kernel functions are used to transform the data higher-dimensional space to enable linear separation. The choice of kernel function, such as linear kernels, polynomial kernels, Radial Basis Function (RBF) kernels, or sigmoid kernels, highly depends on data characteristics.

Although ANN is the most commonly used ML method for transient stability classification, it generally involves a broad training process and an intricate design procedure. Moreover, ANN usually performs well for interpolation but not so well for extrapolation, which reduces its generalization ability. They are more susceptible to becoming trapped in a local minimum. Although, majority of ML algorithms can overfit, if there is a dearth of training samples, but ANNs can also overfit if training goes on for a very long duration [42]. On the other hand, in the recent years, SVM classifiers have received a huge attention from power systems researchers because of producing single, optimum and automatic sparse solution by simultaneously minimizing both generalization and training error and unscrambling data by the large margin at high dimensional space [44-45]. Due to some of these downsides of ANN, it becomes essential to develop a more efficient classifier for transient stability status prediction. SVM does not suffer from these drawbacks and has the following advantages over ANN [11]: (1) less number of tuning parameters, (2) less susceptibility to overfitting, and (3) the complexity is dependent on number of support vectors (SVs) rather than dimensionality of transformed input space.

There are some other algorithms which suffer from various limitations which make SVM a popular algorithm. For instance, decision tree has a tendency to overfit data. This algorithm can be unstable as small variations in data might lead to incorrect results. It can also generation a biased tree if some classes are dominant. Random forest does not explicitly optimise for margin. It can be computationally intensive, particularly for large data sets. Although, this algorithm is resistant to overfitting, it can still occur in the presence of noisy data. *K*-Nearest Neighbour (*K*NN) has some downsides such as computational expense, slow speed, memory and storage issues for large datasets, sensitivity to the choice of *K* and the distance metric, and vulnerability to the curse of dimensionality and noisy data [46-48]

SVM classifiers depend on training points, which lie on the boundary of separation between different classes, where the evaluation of transient stability is important. A decent theoretical progress of the SVM, due to its basics built on the Statistical Learning Theory (SLT) [41], made it possible to develop fast training methods, even with large training sets and high input dimensions [49-51]. This useful characteristic can be applied to tackle the issue of high input dimension and large training datasets in the TSA problem. The basic implementation of an SVM, commonly known as a hard margin SVM, requires the binary classification problem to be linearly separable. This is frequently not the case in practical problems, and therefore, SVM provides a kernel trick to resolve this issue. The strength of the SVM algorithm is based on the use of this kernel trick to transform the input space into a higher dimensional feature space. This allows for defining a decision boundary that linearly separates the classes. The SVM algorithm attempts to find that decision boundary or hyperplane with the highest distance from each class [11].

V. Literature Review: Application of SVM for TSA

This section will review the application of SVM for problems involving TSA. Recently, SVM has been applied to power system transient stability classification problem. An SVM-based transient stability classifier was trained in [5] and its performance was compared with a Multi-layer Perceptron (MLP) classifier. Reference [52] devised a multiclass SVM classifier for TSA classification. Reference [53] recommended a SVM classifier to predict the transient stability status, using voltage variation trajectory templates. Reference [11] trained a binary SVM classifier, with combinatorial trajectories inputs, to assess the transient stability status. Reference [54] employed the SVM to rank the synchronous generators, based on transient stability severity, and consequently, classified them into vulnerable and nonvulnerable machines. Reference [55] proposed two SVMs, using Gaussian kernels, for classifying the post-fault transient stability status of the system. Reference [56] presented an SVM-based approach, for transient stability detection, using post-disturbance signals, from the optimally located distributed generations. Reference [57] proposed a multi-SVM power system TSA method, based on relief algorithm. Firstly, the suggested approach selected numerous feature subsets, with various size based on relief algorithm; then, used these chosen feature subsets for SVM training, and eventually, these trained SVMs were integrated to evaluate the transient stability of power system.

Reference [58] focused on the assessment of the transient stability of power systems, using pre-fault and fault duration data, measured by Wide Area Measurement System (WAMS). In the suggested approach, the time-synchronized values of voltage and current, created by synchronous generators, were measured using Phasor Measurement Units (PMUs), installed at generator buses, and given as input to the suggested algorithm, to obtain a proper feature set. Then, the devised feature set was applied to (SVM) classifier, to envisage the transient stability status. In [59], a different time series forecasting algorithm, using SVM, was proposed, which utilized synchronized phasor data, to provide fast transient stability swings prediction, for the use of emergency control. In [60], a conservative prediction model, for power system transient stability, was suggested, targeting at enhancing accuracy, for predicting the unstable cases. The model was recognized as an ensemble learning model, using multiple SVMs as sub-learning machines.

In [61], a twin convolutional SVM as supervised trajectory-based deep neural classifier was presented, which can remove the computational intricacy of kernel trick. The results demonstrated that the classification accuracy of the presented approach with a larger size window for each test systems exceeded 87% and it outperformed kernel-based approaches on test cases. In [62], an online power system TSA problem was mapped as a two-class classification problem and a novel ML algorithm known as the Core Vector Machine (CVM) was suggested to solve the problem based on PMUs big data. Compared with other SVMs, the devised CVM based assessment technique had the higher precision. Also, it had the least time consumption and space complexity. Based on the data collected from the PMU, a TSA method merging Stacked Automatic Encoder (SAE) and SVM was presented in [63]. Multi-layer abstract learning was performed on the original features by the SAE, and the extracted feature was used to train and test the SVM model.

Reference [64] proposed TSA of a large practical power system using two ANN approaches: Probabilistic Neural Network (PNN) and Least Squares SVM (LS-SVM). Transient stability of the power system was first evaluated based on the generator relative rotor angles (obtained using time domain simulations). Classification results demonstrated that the PNN gives faster, and more accurate results for TSA when compared to the LS- SVM. Considering the fact that the traditional SVM method cannot avoid false classification, [65] suggested a novel approach to solve the weaknesses of traditional SVM, which can enhance the interpretability of results, and avoid the problem of false alarms and missed alarms. In this approach, two enhanced SVMs, known as the Aggressive SVM (ASVM) and Conservative SVM (CSVM), were presented to increase the accuracy of the classification. Cases studies on IEEE 39-bus system and a real provincial power network illustrated the efficacy and viability of the suggested technique.

In [66], a unique TSA algorithm was presented, where SVMs were employed as pattern classifiers. SVMs with different kernel functions and kernel parameters were constructed and trained to compute hyperplanes that split the stable and unstable states of power system for $(n-1)$ faults. The simulation results obtained using three benchmark systems demonstrated the good capacity for fuzzy combined SVM classifiers in TSA. Compared with traditional SVM, [67] devised an advanced TSA system using Multi-layer SVM (ML-SVM) approach. In the proposed method, a Genetic Algorithm (GA) was used in ML-SVM to identify the valued feature subsets with differing numbers of feature. Transient stability of the system was determined based on the generator relative rotor angles. The simulation results demonstrated that the presented approach could lessen the likelihood of misclassification. Reference [68] proposed a comparative analysis of two different ML algorithms, i.e., ANN and SVM, for online transient stability prediction, considering various uncertainties, such as load, network topology, fault type, fault location, and Fault Clearing Time (FCT). The results for the IEEE 14-bus system demonstrated that both ANN and SVM can rapidly estimate the transient stability; however, ANN outclassed SVM as its classification performance and computational performance were established to be greater. In [69], an improved SVM method was suggested for TSA of power system. Firstly, the original feature set was determined by a simple calculation of the original operating parameters of the power system, such as projection energy function feature and system-level feature. Then, the feature sets were used to the TSA problem of SVM with pinball loss (Pin-SVM). To reduce the computational burden, the sequential minimal optimization (SMO) was introduced to break a large Quadratic Programming (QP) problem into a series of small QP problems. The feasibility and validity of the proposed method were demonstrated using the IEEE 145-bus system and an actual power grid in China.

In [70], a power system evaluation model using improved SVM algorithm was proposed for the transient state evaluation system of power system. Firstly, the characteristic vector was extracted from the transient steady-state data of power system, and consequently, the traditional SVM algorithm was enhanced by adding Mahalanobis distance. Finally, the algorithm accuracy and precision were compared. Results obtained showed a higher accuracy and precision of the improved SVM algorithm, and its superior processing ability and evaluation ability of power system data. A SVM-based Convolutional Neural Network (CNN) to assist the operation of the power system was proposed in [71]. The SVM-CNN was realized based on the parameters of time-domain analysis, fault type, fault location, and system load fault clearing time. The suggested work minimized the workload of operational staff and improved efficiency and ability.

VI. Research Gaps and Future Recommendations

Based on the detailed literature review and to the best of author's knowledge, there exists no research work on PTS which uses SVM-based ML approach, considering the uncertainties of load, faulted line, fault type, fault location (on the line), and FCT. Moreover, [72] specifically mentions the potential of SVM for online TSA. In addition, [73-77] strongly indicate that ML is a promising and upcoming approach for online Dynamic Security Assessment (DSA). Thus, one of the main research gap is to predict PTS status using an SVM-based ML approach.

Also, there is a dearth of work which incorporates renewable energy in TSA prediction using SVM. As the amount of renewable energy is increasing continually in the power system, the dynamics of power system are becoming more intricate. More comprehensive studies and simulations are required to understand the behaviour of the system under renewable energy integration. Network topology changes are often ignored in the existing research work. It is significant to train the SVM model for changing topologies. In this regard, the network base topology can be investigated towards accomplishing an optimized network topology from the standpoint of transient stability of the whole system. Novel techniques must be researched and applied such that the SVM model can adapt to any topology of the power system.

In future studies, it is also recommended to incorporate unobserved real-time operating conditions of power networks such as information lost due to the communication failure (unavailability) and absence of quality of power system dynamic responses (noisy data). As different feature subsets have different useful information of a power system; therefore, comprehensive use of this information for TSA must be made. Misclassification and missed classification have entirely dissimilar impact for the stability of the system. Therefore, using different feature subsets to train SVMs and consequently, integrating the result can considerably reduce the misclassified samples, which is of great significance for TSA in practical power systems. The performance of the SVM-based ML approach depends on the quality and quantity of the data. In power systems, the required data are either unavailable, unlabelled or have low quality. Hence, the necessary information is collected using equivalent system models. However, the design of the database generation process can produce biased models, which can cause an overestimation of its performance during assessment. Consequently, it is essential to research further into their robustness and reliability [78].

There are some potential challenges and limitations in the practical applications of SVM to TSA. The main challenge in this regard is acquiring accurate and precise amount of data for training the SVM. SVM models can overfit (overly complex) or underfit (too simplistic). Striking the right balance is critical for model performance. Overfitting occurs when a model fits the training data too closely, capturing noise instead of useful patterns. Underfitting, on the other hand, results from overly simplistic models that cannot capture complex relationships in the data. Addressing these issues often involves hyperparameter tuning and cross-validation (a resampling procedure used to evaluate ML models on a limited data sample). Realizing SVM frameworks for a large scale power system can be demanding due to constraints in resources as training intricate models requires substantial computational power and storage capabilities. Data quality is another critical factor in addressing the challenges of SVM models when applied to statistical power system data. Class imbalances, outliers and missing data points are key contributors in input data of the power system.

Another key challenge is to incorporate changes of the network topology using SVM. The security of the power system is highly related to the topology of the system [79], and changes in the network topology can happen frequently for various reasons, such as for maintenance purposes or unexpected component failures [80]. The impact of changing topology on transient stability rules is a substantial challenge. This is because if topological changes are not considered and transient stability rules are trained only for one specific topology, the resulting assessment of the transient stability (and security) using these rules may provide erroneous predictions, which ultimately leads to incorrect decision-making. Therefore, a key future direction is to enhance the SVM workflow, by considering changes in the system topology [81].

The present study provided a review of some major research works and potential future research avenues associated with SVM application to TSA. This can be a remarkable offset for researchers in the domain of ML, power system stability and operation, particularly in the presence of uncertainty. Recent research [82-91] reveals that there is a lot of scope in this domain, and its potential must be fully investigated.

VII. Conclusion and Future Work

TSA of the power system is a critical issue with escalating demands and numerous operating restrictions. With the increasing uncertainty, renewable energy generation, and electricity market deregulation, its accurate evaluation cannot be overestimated. The constraints of online TSA for modern power systems have become quite strict. Moreover, inability to fulfil these requirements can cause instability which can result in cascading outages and blackouts, hence, causing economic, social, and technical losses. Novel soft computing approaches based on ML, such as SVM, can play a valuable part in ensuring that these requirements are met. Therefore, this paper provided a review of works related to application of SVM to TSA. It is believed that this review will provide a good basis for researchers in the field of SVM and power system transient stability, and consequently, help them understand the existing research status and questions.

As a future work, numerous reviews can be conducted using other ML approaches and a comparative analysis can be drawn. Moreover, ensemble ML approaches can be explored for TSA which combine two or more ML approaches to achieve better performance. Merging quantum computing with ML for TSA is another open area of research.

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