A Comprehensive Review of Machine Learning Applications in State Assessment and Control of Power Electronic Converters

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Abstract. World wise consumption of electrical energy has led to the integration of renewable energy resources into the power grids. These renewable energy resources are interfaced to power grids via power electronic converters because of their abilities of precise control, high efficiency, and sustainability, however, they are also nonlinear, they change the dynamics of the power grids, and require to be operated in aperiodic and unbalanced regime. They often trigger instability in the power grids via interaction through various phenomena including sub synchronous oscillations, intermittent nature of renewable energy resources, harmonic pollutions, and nonlinear dynamics of constant power loads, all requiring appropriate diagnosis and control methods. Several machine learning algorithms have shown remarkable achievements in the quantification of nonlinearity in power electronic converters. This paper describes the comprehensive reviews of various machine learning approaches in the field of state assessment and control of power electronic converters.

Keywords: Machine Learning (ML), State Assessment and Control, Power Electronic Converters, Physics Informed Machine learning (PIML)

1 Introduction

The autonomous operation of power electronic converters interfacing renewable energy resources or constant power loads to power grids requires assessing their dynamic state before taking a specific control action [1]. Broadly used state assessment methods include the White-Box, Black-Box and Grey -Box methods. White-box assessment is parametric while the block-box assessment is data-based method. The effect of any unknown system parameter is regarded as white-process-noise, causing estimation bias in white-box assessment while generalization becomes crucial beyond the training boundaries in black-box method, making it unsuitable for applications where system operation is critical. Besides, the black-box method is also computationally intensive. The combination of both the afore mentioned approaches forms gray-box approach, eliminating the issues of both the methods and reinforce their advantages [2], However, the data acquisition for both the gray box and the black-box approaches is challenging in power electronics. Numerous research works

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have been carried out to extract the data from system input-output responses and a few of them have been discussed in section V.

Massive developments in data acquisition tools, like Internet of Things, edge computing, sensor technology, big data analytics [3], Digital Twins [4] and signal processing, have led to the generation of a wide variety of data. These tools, if used in power electronic converters in power grid architecture can provide large volumes of data that can be used in their autonomous applications, enabling potential opportunities for machine learning to be ensembled in power electronic converters. ML is capable of exploiting data, thereby improving competitiveness of the product via optimization of designs, intelligent controls, system stability analysis, health monitoring and state estimation of system. It gives rise to a potential research area of data driven and AI applications in power electronics, specialized in areas where conventional approaches either fail or have limitations [5]. Currently a lot of research is being carried out in the field of ML applications in power electronics. This paper discusses a few of them that focus on Machine learning based state assessment and control of power electronic converters.

The rest of the paper is organized as follows. In section II various functions performed by machine learning in power electronic converter controls and state assessment have been discussed. Section III describes the methods of data acquisition from power electronic converters systems. In section IV different machine learning methods used in various research publications have been overviewed. Section V presents the detailed research methods proposed in the power electronic converter controls and state assessment along with their outcomes. In section VI the critical analysis of each method has been done, showing their bottleneck challenges. Section VI concludes the research paper.

2 Functions performed by Machine Learning in State Assessment and Control of Power Electronic Converters:

Machine learning is meant to let the computer learn by its experience with data and extract information from it. It discovers the relationships among the data by exploiting principles, regularities or by trial and error [5]. The tasks performed by machine learning can be classified into the following 4 categories [5].

1. **Data Optimization:** The aim of optimization is to maximize or minimize the output of an objective function according to the user's requirements. Optimization has an important role in control of power electronic converters, to operate it for the desired performance.
2. **Data Classification:** Classification aims to label the input data indicating its association to one of the N finite output classes. It is lossless compression and plays an important role in state assessment, health monitoring, maintenance, and fault diagnosis of the power electronic converters.
3. **Data Regression:** The aim of the regression is to find the relationship between the input and output variables and using that relationship, predict the values of

one or multiple output variables for a given input data. In power electronic converters, it is used in control, state assessment, maintenance, and fault diagnosis. The role of regression can be analyzed in the example of frequency control of virtual synchronous generator under varying grid conditions [6].

4. **Data Structure Exploration:** It comprises clustering of data, finding similarities among the data groups, estimating density and distribution of data for given input space. Data structure exploration is important in state assessment, fault diagnosis and maintenance of power electronic converters.

3 Data Acquisition of Power Electronic Converters:

Signal processing outcomes of voltage and current waveforms, used in Phasor Measurement Units (PMU), contain dormant and invisible information that can be useful to infer the real time dynamics of the power electronic system [7], however, this demands sufficient knowledge of electrical systems and signal processing [8]. The various signal processing tools that have been used in different research works for extraction of features from the current/voltage waveforms of the power electronic converters can be broadly classified into Lyapunov method, spectrum methods and wavelet decomposition methods [7]. In Lyapunov method the amplitudes of the Lyapunov exponents indicates the information about the state of the system while in spectrum methods amplitudes of different frequency components are analyzed that are helpful in extraction of different features, depicting the state of the system. Some majorly used spectral analysis methods for power electronic converter state analysis are periodogram method, Welch method, Fast Fourier transform (FFT) method, etc [7]. In wavelet decomposition methods, a mother wavelet is iteratively scaled and shifted to extract features that are localized both in time and frequency domain. Wavelet transform has several variants, but Daubechies wavelet transform, Symlet wavelet transform and Pseudo-Continuous Quadrature Wavelet Transform (PCQWT) are more notable in terms of their performance in feature extraction in power electronic converter's state assessments. After the features being extracted by signal processing algorithms, they are required to be classified. Different machine learning algorithms offer classification services; however, the Machine Learning model should be able to preserve time information and have continuous learning ability.

Data acquisition of power electronic converters requires a mechanism that extracts features from signals and classifies them into transparent and interpretable attributes that can be used as state indicators [9]. Several researchers have turned to this approach to assess the converter state by analyzing signal processing outcomes [10][11]. However, until now, stability assessment based on attribute classification has been limited to a smaller set of possible attributes, with the difficulty of attributes generalization [12] and intensive computations. Currently a lot of research is being carried out on state assessment of power electronic converters using signal processing and machine learning.

4 Machine Learning Approaches used in Power Electronic Converter Controls and State Assessments:

According to the literature review different classes of ML have been used in power electronic converter controls and state assessments in different research works and those can be broadly classified into following four main categories.

1. **Supervised Learning:** The job of supervised machine learning is to map the implicit relationship for the given inputoutput pairs and is useful for modelling nonlinearities in power electronics where it becomes challenging to formulate otherwise. The major tasks of supervised machine learning in power electronic converters, as found in literature, consist of classification and regression. It has been used in applications of fault diagnosis [13], state assessment [14], control [15], maintenance etc [16].
2. **Unsupervised Learning**: In power electronic converters unsupervised ML have been majorly used as data preprocessors for data clustering and classification. Examples include k-means clustering, Self-organizing Maps [17], Principal Component Analysis [18]. In power electronic converters these data preprocessor algorithms are usually applied to reduce the computational burdens and improve results by eliminating redundant data [3].
3. **Reinforcement Learning**: Reinforcement learning aims to map a strategy that maximizes a certain reward in response to a specific input by continuous and progressive accumulation of experience. The strategy is mapped via interaction with the system through trial-and-error process [19]. It is analogous to a Markov decision process [20]. In power electronic converters reinforcement learning is mostly used in control applications, examples include MMPT [21], motor speed and torque control [22].
4. **Physics Informed Machine Learning**: Physics-informed Machine learning combines data model and physical model of the power converter system [23]. It integrates the advantages of both the modelling methods and eliminates their deficiencies [24]. Power electronic converter state assessment and control via physics informed machine learning have shown remarkable results in some research works because of being data light and capable of dealing with heterogenous data, removes the estimation bias of physical modelling and have better dynamics [25-26].

5 Machine Learning Based State Assessment and Control Methods of Power Electronic Converters:

This section discusses the various state assessment and control methods of power electronic converter systems based on the signal processing of the current and voltage waveforms followed by their processing through various machine learning algorithms and a few of them are highlighted as follows.

The research work proposed by Sunny Katyara et al. (2020) in [27] provides a method for estimation and classification of harmonics using machine learning. Fuzzy logic and neural networks were built to estimate the harmonic levels and THDs from the waveforms, followed by features extraction and classified using Support Vector Machine (SVM). The proposed method worked well; however, the accuracy could be further enhanced by using a relatively higher sampling rate and signal processing algorithms. Besides, convolution neural networks used are weaker in modelling the time series data [5].

Raoult Teukam Dabou et al. (2021) proposed high dimensional stability indices by using signal processing methods to extract features from the post fault voltage and current signals in [12]. The extracted features were then used by machine learning and other AI based prediction models including Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), and AdaBoost for stability assessment, however, the deployment of too many signal-processing tools on post-fault signals, used in simulation environment, requires intensive computations.

Xin Li et al. (2021) in their research article proposed a Transient Stability Assessment (TSA) method of power system [29]. The method used Convolution Neural Network (CNN) as classifier. The method was characterized by continuous learning abilities and preserved the time information by integrating orthogonal weight modification (OWM) with CNN. The proposed research work achieved the performance goals, however, new and rarely occurring events would be supposed to potentially undergo longer iterative process. Only stability assessment method has been proposed, control schemes are not elaborated.

Wang et.al (2022) in their research publication proposed a smart sensor employing analytical method that uses the electrical input signals for real time assessment and control of the power system in a decentralized manner [30]. The research work achieved the desired feature extraction via utilizing "Pseudo-Continuous Quadrature Wavelet Transform" (PCQWT). The features after being extracted by PCQWT underwent Convolutional Neural-Network (CNN) that classified features and detected events in real time. The proposed research work achieved the performance goals, however, the method also involved intensive computations, and preserving the time information by CNNs using images is not a smart way.

The research work in [31] presented the voltage stabilization method, for DC/DC converters, feeding constant power dynamic loads, by incorporating Deep Reinforcement Learning. It developed an Ultra Local model controller using sliding mode observer under input reference voltage variations. The proposed method worked well; however, the use of sliding mode observer makes it difficult to regulate abstract parameters [28]. Sliding mode observer is also prone to chattering.

Research article proposed by Qianwen Xu et.al. (2021) considered reliability of Virtual Synchronous Generator (VSG), thereby, proposing dual Artificial Neural Network (ANN) based control system design to control inertia and predict life cycle (LC) time of semiconductor devices [6]. The proposed method quantitatively related impacts of inertia to reliability. The proposed research achieved the desired goals but heavily relied on the statistical models of data. Besides, Conventional ANNs require longer training and testing times.

The research work proposed by Fengjun Yao et.al (2021) used Radial Basis Function Neural Network (RBFN) based droop controller for the frequency stability of Virtual Synchronous Generator (VSG) [32]. RBFN was used to map variations in angular frequency to output inertia. The method worked well by emulating inertia (J) and Damping Coefficients (Dp) and controlled frequency overshoots during transients, however, relied heavily on the physical parameters of the system. RBFN takes smaller time intervals in data training, however, takes considerable time in data testing.

Table 1. Summary of Research Works Reviewed, in terms of Achievements and Limitations

Ref. No.	Year	Achievements	Limitations
[6]	2021	Self-learning and autonomous Effectively maps frequency deviation to inertia emulation. Maps virtual inertia emulation to temperature of IGBT. Predicts Life cycle time of semiconductor device w.r.t ambient temperature	Relies on the statistical models of load profiles. Relies on physical parameters. Conventional ANNs are less accurate and have longer training and testing times. Limited to inertia emulation only Does not provide the complete state assessment information.
[12]	2021	Successful online state assessment of the system Extract up to 500 features from the post fault signal and form stability indices	Applicable to simulation environment only Intensive computational resources are required. Extended the response time. Does not provide control information
[27]	2020	Harmonics estimation with high accuracy Reduced computational burden during training due to CNN	Weaker in time-series data modelling due to CNN Limited to harmonic estimation only Low sampling rates
[29]	2021	Continuous learning abilities Evaluate Transient Stability using CNN. Register new operational scenarios. Cost effective and scalable	Control schemes are not proposed. Limited to Stability assessment Old and rarely used information is wiped out. New and rarely occurring events undergo longer iterative process.

[30]	2022	Self-learning and autonomous Performs online real time sate assessment. Decentralized Works well under channel congestion	Involves intensive computations. Require high computational resources.
[31]	2020	Voltage regulation under reference voltage variation High compatibility due to SMO Learning ability of feedback controller	Difficult to incorporate system constraints due to SMO. Chattering due to SMO Limited to DC/DC applications only
[32]	2021	Self-learning and autonomous Effectively maps frequency deviation to inertia emulation. Adaptive mapping of damping coefficients Controls frequency over-shoots	Relies on statistical data. Limited to inertia emulation only Does not provide state assessment information. Extended response time due to longer classification time
[33]	2020	Self-learning and autonomous Improved prediction accuracy Performs long term voltage stability prediction.	Limited to the voltage stability assessment only Involves intensive computations. Require high computational resources. Extended response time
[34]	2022	Self-learning and autonomous Data-Light and require a relatively lesser number of features. Can be trained using a small training data set. Does not involve intensive computations	Relies on expert knowledge. Limited to DC/DC applications only Control schemes are not proposed.

Kalana Dulanjith Dharmapala et.al (2022) in their research work proposed a novel method, for long term voltage stability prediction based on combination of multiple machine learning algorithms [33. Machine learning algorithms were aimed for regression purposes for selected sets of input voltage stability indices, however, data processing by too many machine learning algorithms makes the method computationally intensive.

Shuai Zhao et.al (2022) in their research publication proposed novel approach for the parameter estimation of a DC-DC buck converter, employing Physics Informed Machine Learning (PIML) [34]. Physics Informed Neural Network (PINN) was formulated via seamless integration of neural network and the buck converter dynamic physical model. Their proposed method was relatively data light, thereby achieving faster dynamic response at the cost of expertise in the research area and is also limited to DC-DC buck converter applications only.

The brief summary of research works reviewed above in the domain of Machine learning based state assessment and control of power electronic converters is presented in terms of their achievements and shortcomings in table 1 above.

6 Critical Analysis

This section performs the critical analysis of the research works discussed in section V, in terms of their bottleneck challenges in real time implementations. Machine learning implementation in power electronic converters makes them artificially intelligent and autonomous. The research work presented in [6] autonomously mapped the inertia to the Life Cycle Time of the semiconductor devices of VSG using ANN. However, in doing so it relied on the statistical model of the frequency profile and knowledge of the system physical parameters. Moreover, the use of conventional ANNs requires longer testing and training times. The research work proposed in [12] showed significant performance by employing diverse signal processing and machine learning tools to assess the post fault state of the power system on IEEE-39 and IEEE-68 buses, however, method not feasible for real time applications because of intensive computations and longer processing time to comply with grid codes and standards [28]. The research work proposed in [27] achieved the desired performance goals by employing machine learning to estimate and classify the harmonics, however, used relatively lower sampling rates. The proposed method is also limited to harmonic estimation and classification, other state information is not assessed.

The research work proposed in [29] showed remarkable results by employing PMU data and CNNs to assess the transient stability of the power system, however, the newly occurring events will potentially follow a longer iterative process that would cause extended response time, and the method is also data intensive. The research work presented in [30] used a specialized variant of wavelet transform PCQWT, for maximum feature extraction from the waveforms and used CNNs for feature classification, however, the method involves intensive computations and time information was saved using channel imaging.

The AI controller proposed in [31] attained the desired performance goals of voltage control under the constant power load conditions due to high compatibility of sliding mode observer and the self-learning capability of feedback controller. However, using sliding mode observer causes difficulties in incorporating the constraints in the system [28]. Sliding mode observer is also characterized by the phenomenon of chattering.

The frequency stabilization method proposed in [32] achieved the performance goals by using RBFNs to perform the nonlinear mapping of frequency variations to inertia of VSG, however, the use of RBFN takes longer time in data classification and testing and very little PMU data was utilized in state assessment of power systems. The voltage control method proposed in

[33] for long term stability prediction of VSC achieved the performance objectives; however, management of transients and PMU data reliability needed a lot of improvements in real-time application and the method is also data intensive. The research work proposed in [34] proposed a relatively newer paradigm for the state assessment and control of power electronic converters by using physics informed neural networks for the parameter's estimation and control of DC-DC buck converters where data model obtained from ANNs worked in synergic manner with the physical parameter's model. However, the research work focused on DC-DC conversions only, in grid tied DC-AC conversions the situation becomes more complex due to involvement of more parameters such as inertia, operational frequency, active and reactive powers, power system harmonics and diverse nature of loads tied to grid.

In this section after critically analyzing the research works presented in section V and summarizing their works in terms of achievements and limitations in table 1 it can be inferred that adding ML to power electronic converters improves their performance but simultaneously it adds computational overheads for the controllers leading to extended response time of the converter system. Applying data driven controls and machine learning to power electronic converter systems helps in quantification of nonlinearity of the system which otherwise is very difficult to perform, however, data of power electronic converter systems is very limited and is heterogenous in nature having the difficulty of attribute generalization. Most important bottleneck challenges in application of ML and signal processing in Grid-tied power electronic converters is adherence to the grid codes and IEEE Standards IEEE Std 1547-2018 [35] and IEC 62040 [36]. These standards define the threshold values for the settling times for changes in frequency, voltages, active and reactive powers, THDs, etc. The processing speed and programming algorithms have a significant impact on the overall performance of the converter system. The use of physics informed machine learning makes the assessment method semiparametric and only those system parameters are modelled using signal processing and machine learning techniques that are difficult to model via classical Whitebox methods. This overcomes the issues of data heterogeneity and intensive computational requirements and enhances the dynamic response of the system.

7 Conclusion

In the research paper "A Comprehensive Review of Machine Learning Applications in State Assessment and Control of Power Electronic Converters"1 extensive study has been carried out. First, the functions of machine learning used in power electronic converters applications, that create artificial intelligence have been discussed. Second, different classes of machine learning including supervised, unsupervised, reinforcement and physics informed machine learning used in power electronic converter systems are reviewed. Then, methods of data acquisition and classification are discussed. Finally, the achievements and limitations of the research works discussed in literature review are compared in domain of state assessment and control of power electronic converters. The comparison showed that physics informed machine learning has more promising results because it is data light, has relatively shorter training and testing times, better dynamic response and can handle the issues of data heterogeneity even with a processor of relatively lower resolution.

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