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Artificial Intelligence Techniques for Enhancing the Performance of Controllers in Power Converter-Based Systems—An Overview

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ABSTRACT The integration of artificial intelligence (AI) techniques in power converter-based systems has the potential to revolutionize the way these systems are optimized and controlled. With the rapid advancements in AI and machine learning technologies, this article presents the analysis and evaluation of these powerful tools as well as in computational capabilities of microprocessors that control the converter. This article provides an overview of AI-based controllers, with a focus on online/offline supervised, unsupervised, and reinforcement-trained controllers. These controllers can be used to create surrogates for inner control loops, complete power converter controllers, and external supervisory or energy management control. The benefits of using AI-based controllers are discussed. AI-based controllers reduce the need for complex mathematical modeling and enable near-optimal real-time operation via computational efficiency. This can lead to increased efficiency, reliability, and scalability of power converter-based systems. By using physics-informed methods, a deeper understanding of the underlying physical processes in power converters can be achieved and the control performance can be made more robust. Finally, by using data-driven methods, the vast amounts of data generated by power converter-based systems can be leveraged to analyze the behavior of the surrounding system and thereby forming the basis for adaptive control. This article discusses several other potential disruptive impacts that AI could have on a wide variety of power converter-based systems.

INDEX TERMS Artificial intelligence (AI), energy management, machine learning (ML), neural network (NN), power converter control, renewable energy integration.

I. INTRODUCTION

The integration of artificial intelligence (AI) techniques in power electronic systems has been an active area of research for several decades. The earliest attempts to integrate AI in power electronic systems focused on rule-based systems, where a set of predefined rules were used to control the system. However, these rule-based systems were limited in their ability to adapt to changing conditions and had difficulty handling more complex systems. Over the years, AI techniques have evolved to include more sophisticated approaches, such as expert systems, neural networks (NN), and fuzzy logic systems. These techniques have been applied to a wide range of power electronic systems, including power converters, active rectifiers, inverters, and motor drives. However, despite the significant progress made in this field, there are still many challenges that need to be addressed to fully realize the potential of AI in power electronic systems.

Recently, there has been an interest in the use of AI techniques in power electronic systems, driven by the rapid advancements in machine learning (ML). These

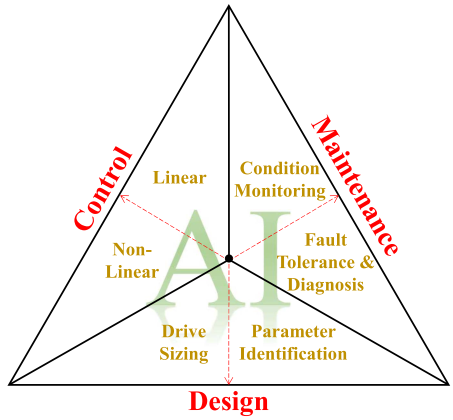

FIGURE 1. Diagram of AI applications in power electronics.

advancements have been made both in the algorithm area and in the computational capabilities of power converter controllers, which led to a significant improvement in the ability of AI systems to handle power electronic systems. The design, control, and preventative maintenance are three key areas where AI is currently being used in power converter-based systems [1]. Three parts are illustrated in Fig. 1.

The design optimization of converter-based systems usually requires a huge computing power to simulate many feasible design candidates and select the optimal one, especially if their fitness needs to be evaluated in various mission profiles. The main reason for the high computing load is that converter needs to be simulated in heat defined design process in itself is complex in nature where mutually coupled performance indices, such as efficiency, power density, cost, and reliability, should be considered [2]. In addition, intelligent control is essential for the reliable, robust, and stable operation of power converter-based systems. For example, when AI algorithms are added to the traditional PI/PR or advanced nonlinear controllers, the dynamic response and tracking performance may be improved in several aspects, such as reliability to changing system conditions, reduction of computational load, or consequent performance improvement [3], [4], [5]. Finally, preventive maintenance of systems, including condition monitoring, fault tolerance, and fault diagnosis, are effective approaches to ensure a system's healthy operation. With the help of AI, the desired prediction and monitoring can be achieved much faster and more precisely than with traditional methods [6], [7], [8].

In [1], a general review of AI algorithms and applications for power electronics was presented from a life-cycle perspective. This article generally considered most AI techniques: expert systems, fuzzy logic, heuristics, and ML, in three distinctive life-cycle phases: design, control, and maintenance. Therefore, it is not specific to the controller domain in power electronics. Supervised and unsupervised learning (UL) techniques for electrical power systems were reviewed in [9]. Although popular ML algorithms were introduced, such as recurrent NN and random forest (RF), the application areas in design, control, and maintenance phases were not clearly categorized and reinforcement learning (RL) was not considered. For microgrid applications, the survey of AI techniques can be found in [10] and [11]. Mohammadi et al. [10] discussed the AI applications in different aspects of microgrids: energy management, load/generation power forecasting, power converter control, fault detection, cyber attacks, and protection schemes. Arwa and Folly [11] reviewed the RL-enabled power management in grid-tide microgrids. Also focusing on RL, Cao et al. [12] reviewed AI applications in power and energy systems, based on the introduction of RL principles and categorization.

Due to the specific control features and challenges of power converter-based systems, such as high-speed switching, complex modulation, and high-computational burden, AI implementation in the control of these systems will be different from the other two life-cycle phases, namely design, and maintenance. Therefore, there is an urgent need for an analysis of AI applications in the control field for power converter-based systems. In recent years, dramatically increasing attention has been paid to AI applications in the control of both individual converters and converter-based (micro)grid systems. This article presents the analysis and summary of the state-of-the-art research on AI and its application status in enhancing controller performance. Regarding the system topology, both inner loop converter control and (micro)grid-level energy management will be considered in this article.

The rest of this article is organized as follows. Section II will list the popular AI techniques (mainly in ML) used in this target domain. In Sections III and IV, this article will focus on two aspects of AI-aided controllers: linear and nonlinear. Both design and control applications are discussed in these two sections. Furthermore, the specific AI application areas will be reviewed in Section V. Finally, Section VI concludes this article.

II. AI TECHNIQUES

AI can be implemented using predefined rules, but in most cases, ML algorithms are used to perform specific AI tasks based on learning from the collected data. ML algorithms can effectively learn rules and relations from training data and improve the trained models automatically through experience. Therefore, the largest use of AI in power converter-based systems is with ML. Other common AI methods include expert systems, fuzzy logic, and metaheuristic methods. To distinguish ML from the metaheuristic search algorithms, Gao et al. [13] proposed a simple algorithm categorization that comprises search algorithm and surrogate algorithm. Both categories were used for the same optimization problem for a converter-based actuation system.

Three main groups of ML algorithms are supervised learning (SL), UL, and RL [1], [14], as shown in Fig. 2. Generally, both SL and UL require collecting data before training. An SL dataset should give outputs/labels corresponding to the inputs, while there is no label defined in UL. For RL, there is no

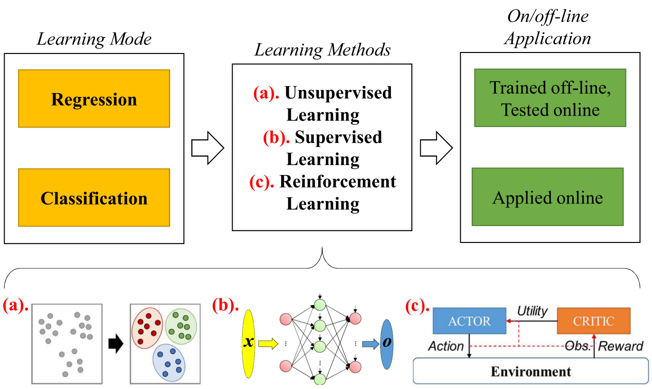

FIGURE 2. Diagram of ML methods, modes, and online/offline applications.

data collection or offline training, because it is determined by the trial-and-error exploration of agents in an unknown environment in order to maximize the cumulative rewards.

As shown in Fig. 2, two learning modes in ML are regression and classification. And in practice, different online/offline approaches should be investigated for different applications. In this article, both online and offline ML model training are reviewed for the parameter design of controllers; but, for controller imitation learning, a common way is using the collected data for offline training. Based on the input/output model design and the data-driven process, ML can be an effective way to enhance the control performance of converter-based systems. Three ML groups will be introduced below, then ML-based emerging techniques will be discussed.

A. SUPERVISED LEARNING

If there are outputs (also called targets and answers) defined in the training data of ML, SL methods are usually applied. These targets can either be continuous numbers or integers. If the targets are all integers/categories, the learning task is known as classification, otherwise, it would be a regression task. Therefore, both regression and classification are training the sampled input–output pairs but their output data features are different. Regression has no requirement for sampled data but, in classification learning, the training outputs should include predefined categories/classes or even only 0 or 1 for some specific problems.

According to the statistics in [1], usage of SL is 91% of all ML applications in power electronics. In particular, artificial neural network (ANN) is one of the most common algorithms in SL where neurons are the fundamental information processing units and the building blocks. Other SL algorithms include linear regression [15], support vector machine [13], [16], and RF [17].

B. UNSUPERVISED LEARNING

For UL, there is no predefined output in the training data. UL learns how to discover patterns and information from a dataset without preset outputs/labels/features. Such methods can also be used to reduce data dimensionality without losing important information. Therefore, the training data for UL can only have certain elements. For example, in a flower category case, there are four elements: sepal length, sepal width, petal length, and petal width. The UL can discover the information that was previously undetected. An example is to categorize different kinds of flowers by using some sampled data of four elements.

UL problems can be further grouped into clustering and association problems. Clustering mainly deals with finding a structure or pattern in unlabeled data. The flower category case is indeed a clustering problem. Association rules can discover associations/relationships between elements in large databases. For example, people that buy a new house are most likely to buy new furniture.

C. REINFORCEMENT LEARNING

The third group of ML is RL, which is learning how intelligent agents can perform a task by interacting with their environment. Unlike classical and heuristic optimization methods, RL does not require an accurate model of the system or environment to generate an optimal solution [11], [18]. In the learning process, these agents ought to take action (updating the policy at the same time) in a specific environment. They would get rewards from each step/trying and the final target is usually to maximize the cumulative reward.

Therefore, in the beginning, how to operate in the environment is unknown, and no trustworthy data can be collected. The agents should try different actions in the environment to receive the corresponding rewards. Based on the cumulative rewards, the agents can learn a good policy (which means how to act in a certain position) in the environment. Obviously, RL is an online learning process. It differs from SL or UL because no input/output data pairs are collected before the learning process.

D. ML-BASED EMERGING TECHNIQUES

The above three sections individually introduced three groups in ML. However, the practical problems may need multiple groups of algorithms to address, and even an independent algorithm could encompass more than one type of learning method. For example, deep deterministic policy gradient usually combined SL [deep neural network (DNN)] with RL [19], [20].

With the fast development of AI and ML, there are emerging ML techniques that came to worldwide attention in recent years. Federated learning (FL), also known as collaborative learning, is one of the emerging techniques. It is first introduced by Google in 2016 [21]. FL typically applies when individual actors need to train models on larger datasets than their own, but cannot afford to share the data in itself with others (e.g., for legal, strategic, or economic reasons). The technology yet requires good connections between local servers and minimum computational power for each node [22], [23]. FL trains an algorithm across multiple decentralized edge devices or servers holding local data samples, without exchanging them. This approach stands in contrast to traditional centralized ML techniques where all the local datasets are uploaded to one server, as well as to more classical decentralized approaches, which often assume that local data samples are identically distributed. There are three parts to FL: centralized, decentralized, and heterogeneous. FL has been effectively applied to self-driving [24], wireless power control [25], and large-scale energy systems [23]. With the continuing development of distributed large-scale converted-based systems, FL could become a promising AI technique for wireless computing and power control.

Another popular technique in ML is transfer learning (TL), it has found several applications in electrical power systems. TL leverages knowledge gained from one task and applies it to a related but different task to pursue high performance and efficiency. TL is desirable for the practical problems that the training data are expensive or impossible to recollect [26]. Some application areas of TL in electrical domain are energy management [27], battery health [28], impedance estimation [29], [30], and thermal performance of motor [31].

III. AI APPLICATIONS IN LINEAR CONTROLLERS OF POWER CONVERTERS

Linear controllers, such as cascaded voltage and current loops, are widely used in power converter systems to regulate the power flow and maintain stability. However, these controllers are designed to operate in linear systems and can have difficulty performing optimally in nonlinear systems. Therefore, for optimal performance, the parameters of linear control loops should be adapted to the changing operating conditions in nonlinear surrounding environments. In this context, AI-based techniques can be used to adapt the parameters of linear controllers in power converters.

Due to the possession of nonlinearity, and the ability of online learning (transferring the real-time experience to AI models), the AI-aided PI/PR online control methods have been widely used in different areas, such as dc–dc converter [3], [32], [33], [34], spacecraft [35], exoskeleton systems [36], and electric vehicle charging system [37]. However, there are generally two groups of approaches utilized to do that, design and control, as discussed below.

A. PARAMETER ADAPTATION

1) ONLINE DESIGN

In this approach, an AI-based signal processing method is used to take measurements from the environment and learn the optimal parameters in real time. This can be achieved by exploring an online AI-based surrogate model of the linear system, which is trained using data from the system and the environment. AI techniques, such as ANNs and heuristic algorithms, can be used to build this model. By continuously searching through the model, the controller can adapt the parameters for different operating conditions in real time. However, it can be computationally intensive and require a high-frequency sampling rate.

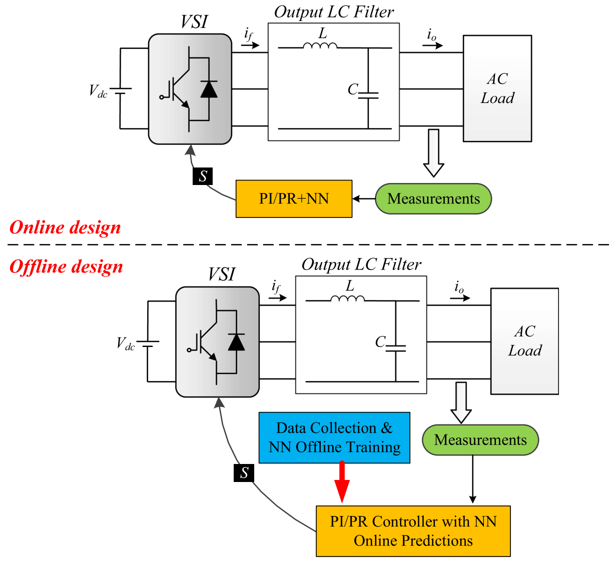

FIGURE 3. ANN applications in linear controllers.

In [38], two types of ANNs were proposed to design a Hammerstein model identifier and a PID controller for the adaptive control of a converter-based hybrid energy storage system (HESS). The online learning of Hammerstein ANN can supply an appropriate power flow reference for the HESS to improve unsatisfactory frequency deviations and tie power oscillation. In [39], the student psychology optimization algorithm is used for the online tuning of control parameters within a PI-incorporated RL ANN controller, for power system applications.

Apart from ANN applications, in [40], local model networks (also recognized as neuro-fuzzy systems) were used to identify the model of the dc–dc buck converter, which can model the nonlinear dynamics for the implementation of a local linear controller regulating the converter output voltage. To improve the transient response performance of dc–dc converters, Liu et al. [41] combined two fuzzy-logic controllers with a PID compensator for the coefficients and error modifications.

2) OFFLINE DESIGN

Here, a surrogate model of the optimal parameter adaptation method is created in an offline setting, using data from the model of the environment and the converter system. This model can be used to determine the optimal parameters for different operating conditions, which can then be implemented in the controller. This approach does not require real-time adaptation, but it does require a large amount of simulation data to be collected and processed in order to determine the optimal parameters. Moreover, if simulation data are not sufficiently well representing the real system, this approach may yield suboptimal or even unstable results.

The online/offline ANN-based design diagrams in a linear controller are shown in Fig. 3. This figure uses a dc–ac voltage source inverter (VSI) feeding an ac load via an output *LC* filter but, the general application of ANN should be similar in other topologies, such as ac (micro)grid connected using an *LCL* filter. The biggest difference between online and offline design is that there is no intensive online training in offline design. As a tradeoff, independent offline learning usually requires a high number of offline simulations to collect the training data. For dc–dc converters, Liu et al. [32] proposed using ANN to adjust both PID coefficients and the controller structure. Maruta et al. [3] proposed an ANN-based predictor to modify the output voltage reference values in a PID controller, which can improve the transient response. In these studies, ANN was trained offline to pursue high prediction accuracy for the output voltage of the dc–dc converter.

B. CONTROL SURROGATE MODELING

Different from the above parameter adaptation studies, in [33], an ANN was trained as an adaptive controller, which directly outputs the duty cycle and the frequency of gate-driving signals. This belongs to the other group of AI applications in the linear controllers, the controller surrogate model. In this approach, a surrogate AI-based model of the system is designed that blends linear control and nonlinear system dynamics, e.g., by matching the linear impedance model of the converter with the nonlinear impedance model of the grid. This model can then be used in an online or offline search for parameters of the linear controller, as indicated in previous subsections. The AI-based model can be created with techniques, such as physics-informed NN, which can incorporate the physical laws of the system into the model.

IV. AI APPLICATIONS IN NONLINEAR CONTROLLERS OF POWER CONVERTERS

If only simple linear controllers are employed, system dynamics and external disturbances may not be well addressed though they are computationally light without much complexity. In contrast, some advanced control methods can integrate nonlinearities and consider system constraints into the model, for example, model predictive control (MPC). One of the key characteristics of MPC is that the control objectives and system limitations can be simply and intuitively included in the cost function (CF), directing the easy generalization for different converter topologies.

Two main categories in MPC include the continuous control set MPC (CCS-MPC) and the finite control set MPC (FCS-MPC). CCS-MPC uses the control vector as a continuous control signal, thus, the output of optimization can be any vector within the control region defined by available voltage vectors of the converter [42], [43]. Differently, FCS-MPC considers a set with a limited number of input candidates thus the output of optimization can only be one of the considered vectors in the set [44]. AI techniques have been used for both the design and imitation control of MPC. The following two sections will look at these two aspects in detail.

A. PARAMETER DESIGN FOR NONLINEAR CONTROLLERS

Weighting factor design continues to be a hot topic in MPC because there are usually multiple control terms in the used CF. Dragičević and Novak [45] proposed an ANN approach to automatically select the weighting factors in the CF of FCS-MPC. The trained ANN serves as a surrogate model of the converter that can provide fast and accurate estimates of the performance metrics for any weighting factor combination. Vazquez et al. [46] presented an ANN-based real-time tuning method of a weighting factor to achieve the desired average switching frequency and track the current reference.

Gao et al. [47] proposed an inverse application method of AI that can effectively provide references and coefficients for the control of a power converter-based system. Two different cases were used for the method validation. One is the current sharing for a converter-based microgrid. The other is the extension of the MMC operation region under unbalanced grid faults. An ANN-based droop coefficient design method was proposed in [48] for improved load sharing.

B. IMITATION CONTROLLER FOR NONLINEAR CONTROLLERS

The high-computational burden is one of the main disadvantages of MPC, especially for the implementation of multistep predictions or/and multilevel converters. To address that, ANNs were used to learn the MPC model via offline training, which can keep an approximate control performance while at the same time reducing the computational burden. The theoretical basis of this imitation approach is that the predictive control process is completely deterministic, i.e., for the same set of input variables (i.e., circuit measurements) and a given CF, the outputs (inserted vectors/submodules) will always be the same. In this context, while the conventional MPC uses exhaustive rolling optimization every time instant to identify the optimal actuation, this is not necessary. It should be possible to represent the deterministic input–output relationship with a more computationally efficient structure. Therefore, the same control effect as the MPC can be achieved by an ANN, but with a lower online-computational burden.

The general way of MPC imitation is depicted in Fig. 4 for an inverter system. There are three steps in this process.

1) Data collection from the original MPC model.
2) ANN offline training.
3) Online test of the trained ANN.

The first two steps are shown in Fig. 4(a) while the last step is shown in Fig. 4(b).

Some published works studying ANN-based predictive controllers are discussed below. A deep NN-based predictive control strategy is generally presented in [49] for the application of high-frequency multilevel converters. However, none of the technical details of ML work was provided, for example, data collection, and ANN training and validation. In contrast, Mohamed et al. [50] clearly presented an ANN learning approach for the control of a two-level VSI feeding linear and nonlinear loads. System descriptions, FCS-MPC principles,

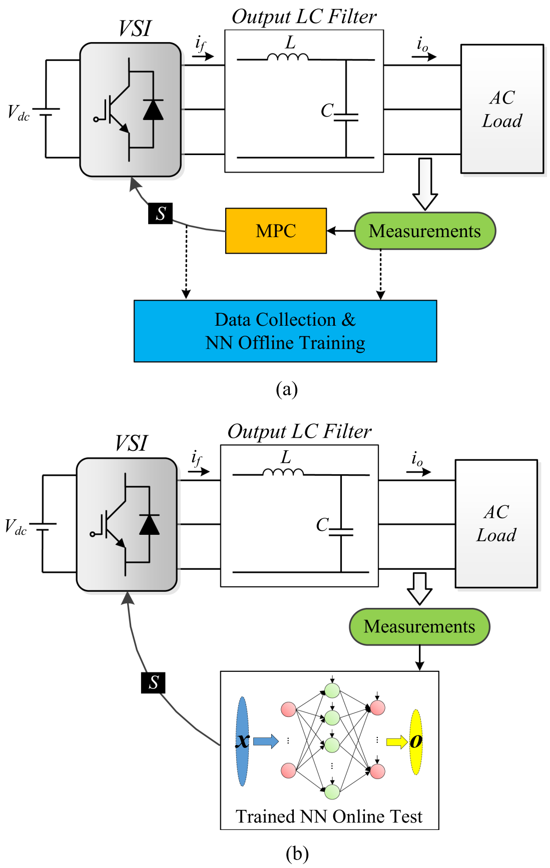

FIGURE 4. Diagram of MPC imitation learning. (a) Data collection and ANN training offline. (b) Trained ANN online test.

proposed ANN architecture, and training/test/validation are all presented in detail. Moreover, the authors collected sample data from 60 circuit conditions (covering the linear/nonlinear load) and tested the trained ANN for all the considered circuit conditions. Even though the proposed method in [50] was not validated in the experiment, it is presented with all necessary technical details, thus easy to implement and generalize. Following the same approach, Novak and Dragicevic [51] trained different ANN controllers for upto N = 3 prediction horizons and tested them in the experiment rig.

Regarding the converter topology, the authors in [50] and [51] used this SL method for two-level converters, and Novak and Blaabjerg [52] further implemented it in the three-level converter. The authors in [49] and [53] trained and validated the ANN imitation controller to a five-level flying capacitor converter. The authors in [54] and [55] proposed two different ANN imitation controllers for the modular multilevel converter (MMC).

C. ONLINE ANN FOR NONLINEAR CONTROLLERS

Apart from the above design and control studies using ANN offline training for MPC, there was plenty of research on NN-based nonlinear online-learning controllers, which do not comprise data collection for the learning but use an optimization method, such as Levenberg–Marquard [56] and genetic algorithm (GA) [57]. For example, Hou et al. [58] proposed an adaptive self-organizing fuzzy wavelet NN for an ac motor servo system, which uses adaptive GA to optimize ANN parameters. In [5] and [59], recurrent fuzzy ANN-aided (for feature selection) sliding-mode control was used in the power converter-based systems for intelligent control with an active power filter, where the online learning laws can effectively capture unknown functions with a low-computational burden.

V. APPLICATION AREAS AND FUTURE PERSPECTIVES

After discussing the AI techniques for linear and nonlinear controllers, in this section, different AI applications are briefly introduced. Fig. 5 shows the general structure of this section. Solar, wind, high-voltage direct current (HVDC), energy storage, powertrain, and promising power to X applications are presented to describe the differences between each other.

Following the above sections, the common technologies will be first introduced in this section, those methods are general methods and thus available for most applications/situations. Furthermore, application-specific AI technologies are given one by one, and those technologies are designed for specific applications to achieve different goals.

A. GENERAL AI TECHNOLOGIES

Four aspects will be summarized below for the general AI technologies. The first two (AI-based controller and controller design using AI) have been elaborated in Section IV. The third (converter modeling using AI) and fourth (stability analysis by AI) are also important and practical topics regarding AI-enabled controller. The pros and cons of each aspect will be presented to help the potential scholars and engineers select suitable methods.

1) AI-BASED CONTROLLER

The grid-connected converters play important roles to regulate the power to the grid. Section IV introduced the ANN application in replacing the traditional PI-based controllers to reduce the computation burden. For the photovoltaics (PV) application, Demirtas et al. [60] gave an example that used an ANN-based controller to control a single-phase PV inverter. The results show that the output power can be regulated by the proposed ANN-based controller. Similar AI-based imitation methods could be generalized to different systems and applications.

The advantage of the AI-based imitation controller is that, the transient response of the AI controller is faster than PI controller because there is no integral part in the controller to slow down the dynamics behavior. However, because the controller is trained by collected data only, there may be a risk of running out of the training range. Thus, the response of AI controller is not fully predictable. In [55], a case is given with some results when the controller runs out of the training range, the MMC is still able to control the system. But, obviously, it is not for all the related control problems.

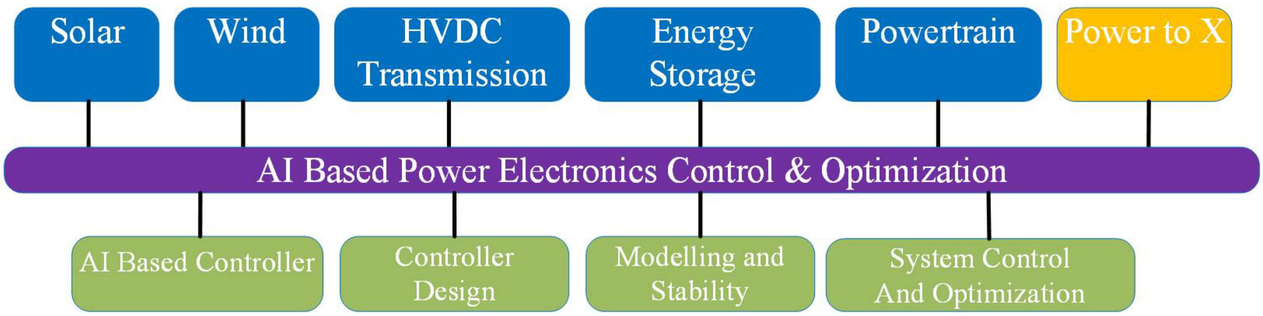

FIGURE 5. AI applications.

2) CONTROLLER DESIGN USING AI

As mentioned in Section IV, apart from replacing the PI/PR controllers with AI, AI technologies can be used to help better design the traditional converters, at the same time, keeping the existing controllers in the converters. For example, in [61], the artificial bee colony algorithm is used to design the PID parameters of the PV converters. Galotto et al. [62] presented an recursive least square and GA-based tool for PID controller tuning, with this method, the controller design process can be accelerated. In [63], a particle swarm optimization controller parameter design method is proposed for the dc–dc buck converter to reduce the aforementioned transient and steady-state errors.

For ML applications, Dragičević and Novak [45] proposed an ANN-based method to design the weighting factors of the MPC-based grid-connected controller. In [47], a special application of ANN is introduced to select the droop coefficients of microgrids, that is, instead of inputting system parameters for system response, the desired system response is set as the input of ANN, then the trained ANN can tell the user what is the preferable input parameters for the target system. The gain of ML approach is that, it can get rid of optimization algorithms, no local optimal problem. This is because, after training, computation of ANN is extremely light, thus, exhaustive algorithm can be used in the design space. The optimal design can be quickly found through tightly sweeping the design space.

3) CONVERTER MODELING USING AI

Regarding the modeling of the power electronics converters, traditional analytical methods can be used to model the converter, however, it heavily relies on the accuracy of the system parameters. By using AI technologies, the modeling of the converter can be obtained by measuring the converters. In [64], Bayesian regularization along with ANN and RF-based ML methods are used to model the power electronics converter with collected experimental data.

In this case, most of the industrial applications will still treat AI converter model as a trained or simulated "black box." That means, this method can only be used to verify the system modeling after the physical system has been built up. Therefore, even though this method is useful for modeling verification, it may not be applicable in the early design phase of the system.

4) AI-BASED STABILITY ANALYSIS

In the modern power electronics-based power system, the stability of the system is an important factor due to the high share of inverter-based resources. For example, the phase lock loop of the grid following the converter will cause system instability under weak grid conditions. AI technologies can contribute to stabilizing power electronics-based power systems. In [65], a RF-based power oscillation damper for grid forming converter is proposed, the proposed damper can automatically adjust the gain of the active damping controller based on the different operating points. In [66], the proposed AI-based control design uses a DNN to learn the nonlinear mapping between the virtual synchronous generator (VSG) input and output signals, enabling it to adapt to different operating conditions and disturbances. This article presents simulation results to demonstrate the effectiveness of the proposed control design in improving the stability and robustness of VSGs under various operating scenarios. Liu et al. [67] gave a comprehensive review of the AI applications to improve the stability of future power systems.

For stability analysis, the key interest from the industry is the physical principles and insights of stability issue in the system. With traditional transfer function or state-space-based stability analysis, there is a solid theory behind it to explain the stability. However, due to lack of interpretation, industries are still hesitant to embrace the AI-based stability analysis, though it is easy to use with promising results.

B. TECHNOLOGIES FOR SPECIFIC APPLICATION

AI techniques can be applied in many specific areas, but the function and purpose may vary according to different requirements. For example, maximum power point tracking (MPPT) should be considered for solar applications; however, AI-based MPPT is not very common in powertrain applications. Some specific AI application areas are listed as follows.

1) SOLAR

For solar applications, the special application of the AI technology is for the MPPT purpose, MPPT is widely used in dc–dc converters in solar applications to track the maximum power from the sun. Traditionally, two main non-AI MPPT algorithms are commonly used: perturb and observe algorithm [68] and the incremental conductance algorithm [69]. However, the traditional MPPT algorithms cannot properly track the maximum power point under partial shading conditions. The AI-added MPPT methods can track the global maximum power point with higher computational speed and faster dynamic speed [70]. Kiran et al. [71] compared different AI-aided MPPT algorithms both under partial shading conditions, the conclusion from this article is that RBFC optimized Fuzzy controller has the highest efficiency under partial shading conditions.

2) WIND

In wind energy systems, one challenge is the changing of the wind speed over time might cause power fluctuation in the wind energy system, then the frequency of the wind network will also be fluctuating. In [72], an adaptive ANN controller for the energy capacitor system in a wind farm is proposed to better control the frequency of the wind farm network. The network frequency variation is minimized by the proposed controller. In [73], an insulated-gate bipolar transistor (IGBT) fault tolerant control strategy for wind turbine converter is proposed, and fuzzy logic is used to fast detect the wind turbine converter IGBT fault, then the protection algorithm will activate the redundant converter leg to bypass the faulty leg.

3) HVDC APPLICATION

The power needs to be transferred to the power grid using high-voltage alternate current (HVAC)/HVDC technologies to reduce transmission losses from the far away generation units. For HVAC technology, traditional power transformers are used, which will not require many power electronics controllers in the plant, then AI application in the HVDC system is not within the scope of this article. For HVDC technology, two main power electronics converters are used: line-commutated HVDC converters, and voltage-source HVDC converters. AI technologies can be used to better control the HVDC converters to achieve internal and external performances. In [74], an ANN-based operational region extension method for MMCs under unbalanced grid faults is proposed, the ANN can automatically decide the injected circulating current to reduce the submodule voltage ripple under grid faults, hence, the submodule over voltage trip is avoided and then the operating region is extended. In [54] and [55], ML-based controllers are proposed for MMCs to achieve faster dynamic response and lower the computation burden of the controller.

4) ENERGY STORAGE SYSTEM

Energy storage is an important role in the future renewable-energy-based power system to shift the mismatch between generation and consumption. The battery is one of the most important ways to do energy storage. Besides energy storage, the battery-connected converter can also provide the grid ancillary services, for instance, reducing the system harmonics, regulating system frequency, and supporting system voltage.

Koganti et al. [75] proposed the design of a multi-objective-based AI controller for a wind/battery-connected shunt active power filter (SAPF). The controller aims to improve the performance of the SAPF by simultaneously optimizing multiple objectives, such as total harmonic distortion, voltage regulation, and energy efficiency. Abdalla et al. [76] gave a comprehensive review of the AI applications of energy storage systems.

5) POWERTRAIN FOR TRANSPORTATION: ELECTRIC DRIVE CONTROL

Several studies have been conducted for electric drive applications by using ML-aided controllers. For example, Hammoud et al. [77] used a multilayer perception feedforward ANN to learn the long-horizon FCS-MPC, which solves the mixed-integer optimal control problem offline to generate the training data of ANN. After training, a two-level inverter-based motor drive was controlled by the trained ANNs in real-time systems, and different horizon numbers were compared. Deep RL was used in [78] for a dc–dc buck converter-fed dc motor to reduce the torque/current ripples. And Nikdel and Nikdel [79] proposed ANN model predictive and variable structure controllers for the single-degree-of-freedom rotary manipulator.

6) FUTURE PERSPECTIVES—POWER TO HYDROGEN

With the large-scale development of renewable energies, the constraint of the power grid limits the maximum power that can be transferred to the grid, and also the intermittent nature of renewable energies requires a long-term energy storage solution for renewable energies. Producing hydrogen by using energy can be an ideal solution for long-term energy storage. AI has good potential to better control and design future green hydrogen systems. The power converters in green hydrogen systems play important roles in safe, high-efficient, and low-cost green hydrogen production. This area is still relatively new and many questions need to be solved in the near future.

Nowadays, the power industry is still mainly using conventional analytical methods to design, model, and control the power electronics system, because of the well-developed theory and interpretation of the conventional methods. An example is the impedance-based method to judge the grid-connected converter stability. In the near future, the power industry will not fully trust AI techniques, nor quickly turn to AI-based methods for power converter control. However, AI-based methods still have great potential for industrial applications, especially when the system is too complicated to be analytically explained. The data-driven models could help electrical engineers to gain the system insights without doing tedious analysis or modeling, this is indeed the key advantage of AI techniques.

VI. CONCLUSION

This article gave an overview of AI-enabled controllers for power converter-based systems. To begin with, the fast-developing ML algorithms were introduced with three basic groups: supervised, unsupervised, and RL. Then, the AI applications in linear and nonlinear controllers were discussed separately from two perspectives: design and control. In this part, online/offline application modes and their technical details were analyzed and discussed. In addition, the common AI technologies were summarized with four aspects that can be generally used for various applications. Some specific AI application areas were further given, which may focus on typical requirements or targets. Finally, a future perspective on power-to-hydrogen was added as a promising way for future green energy applications.

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