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A Survey on Deep Neural Network (DNN) Based Dynamic Modelling Methods for Ac Power Electronic Systems

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ABSTRACT:

This research work contains the assessment of a deep neural network (DNN) based dynamic modeling scheme for AC power electronic systems. The study is based on the premise of utilization of deep learning algorithms to derive models that are accurate and dynamic for capturing the aspects that are complex in AC power electronics systems. Nonlinear relationships and variability in operating conditions make it challenging to apply traditional modeling; thus, a possibility to apply DNNs is considered due to their data-driven learning compared to conventional feature-oriented techniques. It is a process of training and testing of the developed DNN models on the data sets, developed from the AC power electronic systems, under various operational conditions. Satisfaction is measured based on performance indicators that individuals employ, for instance, accuracy, resilience to different loads, and computational speed that justifies the proposed approach. As per the obtained results, the proposed DNN-based models for the four classes have better prediction accuracies compared to conventional techniques for real-time continuous control and fault diagnosis in AC power electronic systems. This work fits within the advancements of the field by offering a detailed evaluation of DNNs as a valid means for dynamic modeling within the scope of AC power electronics in order to critic and improve the performance and dependability of more practicable applications.

Keywords: Deep Neural Network, Dynamic Modelling, Networking, AC Power Electronic, and Deep Learning.

1. INTRODUCTION

Some recent research works have investigated Dynamic Neural Network (DNNs) [1], which are shown to be adequate for capturing temporal behaviors of AC power electronic systems. This stretched abstract surveys the latest developments and techniques in utilizing DNNs for dynamic modeling inside AC power electronic systems, with focus on their ability to face issues arising from nonlinearity, uncertainty, and transient behavior. The present work further includes comprehensive analysis and investigations on various aspects of DNN such as the architectural designs, the training process and validation strategies for AC power electronic applications.

In the second paper, discussions on model development is provided [2] to evaluate the DNN based dynamic modeling. Scholars have used various architectures like CNN, RNN and the combination of both CNN-RNN to learn temporal dependency and spatial correlations in AC power electronic systems. Training methods involve supervised learning where large volumes of data of simulated or experimental tapes being fed into the system to adjust the parameters to the models using back propagation methods. To improve the model's applicability in various system configurations and working conditions, transfer learning and ensemble approaches are also investigated.

In terms of performance evaluation of DNN-based models, this review is also dedicated to AC power electronic systems [3]. Performance criteria such as accuracy, rate of convergence, computational complexity, and so on are thoroughly scrutinized with regard to many examples and standard data sets. When compared with the conventional modeling methodologies that include state-space models and machine learning algorithms, DNNs have excellent predictive characteristics especially when applied to systems with highly nonlinear dynamics and frequent switching. Also, the sensitivity analysis and the robustness testing under the deviations of parameters prove that the DNN-based models can predict the transient behaviors and system response accurately.

Applications of DNN-based dynamic modeling of AC power electronic systems in the fields of real-world engineering are reviewed in [4]. Such applications are real time control, diagnostics, topological, condition monitoring and control for power electronic converters and inverters. Real-world examples are illustrated to show how the DNN models enhance the system performance, reliability, and robustness as compared to traditional techniques. Also, improvements to the basic DNNs by combining them with more complex control methodologies such as MPC, or new adaptive control systems also serve to complement the attainment of high performance goals and meeting strict norms and requirements. Issues and drawbacks that relate to DNN-based dynamic modeling in AC power electronic systems are discussed critically [5]. These are; Large training dataset, complexity involved, black box model interpretability and in complex system configurations there is a high risk of overfitting. Measures that can help to overcome these issues, like data augmentation [6]-[8], the use of the regularization schemes [9], and explainability tools for DNN models, are described to guarantee the DNN models' applicability in real-world projects [10].

Possible directions of further investigation in the area of DNN-based dynamic modeling for AC power electronic systems and other trends are also discussed to point out the further development of the section. These include the discussion on the compromise solutions between the theoretical approaches, such as physics-based models and data-driven ones; the incorporation of the methods who provide constructive information on the uncertainty in predictions and the development of the novel DNN structures with low complexity for real-time implementation on the embedded platforms.

2. LITERATURE SURVEY

The literature review of our research work is as follows,

In AC power electronic systems, Han, Zhongyang, and colleagues [11] have discussed general deep learning and more specifically, CNN. Their work is directed to modeling the temporal dependencies and interactions in system dynamics that allow for accurate prediction superior to conventional approaches.

In the work of Gabriel, et al. [12], the authors attempt to analyse the application of Recurrent Neural Networks (RNNs) in predicting transient responses of power converters. They pay more attention to the capacity of RNNs learning and predicting dynamic behaviors in the course of switch transition, thereby improving system stability and response characteristics.

Rizeakos, V., et al. [13] apply CNN-LSTM structures to detect faults in inverters using deep learning. Their approach uses spatial and temporal characteristics to properly diagnose the faults, which enhances reliability and maintenance.

Transfer learning methods are employed by Yang Weng [14] for generating more generalized deep neural network solutions for numerous power electronics systems. Their studies show that the pre-trained neural networks can be transfer learnt and fine tuned and will reap excellent results even with very little data in various operational environments.

In the paper [15], Chen has looked at the use of deep reinforcement learning algorithm in real-time control of power converters. In their research, they examine the manner in which DRL approaches ensure the optimization of the converter's functions from the system's dynamic states through self-learning and self-development of efficient control mechanisms.

Dang, Yuchen, et al. [16] used ensemble deep learning models to improve accuracy of forecasting of the power system stability. Their work combines different NN structures and training approaches to address the uncertainties and enhance the forecast quality under different load and environmental conditions.

Machlev, Ram, et al. [17] looked at the explainable AI for generating an interpretable dynamic model in power electronic applications. In their work, they carry out both theory and algorithm work to concentrate on the robustness and explicability of the models to ensure that the stakeholders gain confidence in the model for the crucial applications.

Mansouri, Majdi, et al. [18] also used the deep learning for condition monitoring and prognostics in the grid-tied inverters. It shows that the current work of DNN based models can identify initial features of degradation, forecast future performance behavior and accord optimal maintenance schedules so as to extend inverter lifetimes.

Gonzalez-Jimenez, et. al., [19] suggest control methods based on data, which are implemented through deep neural networks in power electronic systems. Essentially, their work focuses on showing possible approaches to assess the capability of DNNs in leaning control policies from the operation data hence arriving at adaptive and responsive control actions in a manner that enhances the efficiency and stability of the system.

Kumar, Gulshan, and Ali Altalbe [20] propose efficient DNN structures directly optimized to run in real-time in the electric vehicle charging devices. They employ their research on the complexity models and the use of intensive computation to meet the required performance in dynamic charging.

They and their papers expound on various uses and improvements in the use of deep neural networks for dynamic modeling in AC Power electronic systems; thus, demonstrating how AI [21]-[24] can bring about significant positive changes in the dynamic and operational efficiency, reliability, and performance of such systems [25]-[27]. Ayyalasomayajula Madan Mohan Tito, et. al., [28] proposed Neural Network based techniques for productivity optimization. Table 1 shows the tabular column summarizing the research works on deep neural network-based dynamic modeling for AC power electronic systems, along with their advantages and limitations:

Table 1: Comparison table of the previous researcher works on deep neural network-based dynamic modeling for AC power electronic systems

Author(s)	Objective	Advantages	Limitations
Han, Zhongyang [6]	Deep Learning for Time Series Modeling in Power Electronics	Captures temporal dependencies, handles nonlinearities effectively.	Requires large datasets for training, computationally intensive.
Gabriel, et al. [7]	Recurrent Neural Networks for Transient Response Prediction	Predicts transient responses accurately, enhances system stability.	May struggle with long-term dependencies, complex to train and optimize.
Rizeakos, V., et al. [8]	Hybrid Deep Learning Models for Fault Detection in Inverters	Integrates spatial and temporal features, improves fault detection accuracy.	Interpretability of black-box models, requires domain expertise for tuning.
Yang Weng. [9]	Transfer Learning for Generalizable DNN Models	Adaptable across different system configurations, reduces data dependency.	Initial pre-training may bias results, transferability depends on similarity.
Chen [10]	Real-time Control Using Deep Reinforcement Learning	Achieves adaptive control strategies, optimizes converter operations.	Requires substantial computational resources, challenges in real-time inference.
Dang, Yuchen, et al. [11]	Ensemble Deep Learning Models for Robust Power System Stability	Enhances prediction robustness, mitigates uncertainties effectively.	Complexity in ensemble model management, potential redundancy in predictions.
Machlev, Ram, et al. [12]	Explainable AI Approaches for Interpretable Dynamic Modeling	Improves model transparency, enhances trustworthiness in decision-making.	Trade-off between interpretability and model complexity, additional computational overhead.
Mansouri, Majdi, et al. [13]	Deep Learning for Condition Monitoring and Prognostics	Early detection of faults, predicts system degradation effectively.	Data quality and availability affect model performance, requires continuous training.
Gonzalez-Jimenez, et. al., [14]	Data-driven Control Strategies Using DNNs	Learns complex control policies, adapts to dynamic system conditions.	Challenges in integrating with existing control architectures, initial setup complexity.
Kumar, Gulshan, and Ali Altalbe [15]	Hardware-efficient DNN Architectures for Real-time Implementation	Optimizes computational efficiency, meets real-time performance requirements.	Hardware constraints may limit model complexity, potential trade-offs in accuracy.

3. MAJOR CHALLENGES IN DESIGNING DEEP NEURAL NETWORK BASED DYNAMIC MODELLING METHOD FOR AC POWER ELECTRONIC SYSTEMS

Proposing DNN [29] based dynamic modeling techniques for AC power electronic systems provides some of the following challenges which researchers and engineers need to resolve to make the systems efficient and effective. Here are eight key challenges in this context:

1. Complexity of System Dynamics: AC power electronic systems are highly nonlinear and also dynamic and dependent on load, switching actions and environment. Such intricacies mean that designing DNN models that will adequately capture such aspects without overfitting the model or underfitting it is complex.

2. Data Availability and Quality: The DNN models proposed are suitable for real-world applications for which sufficient amounts of clean data for training, validation, and testing should be available. However, the challenges are in collecting statistically significant databases that cover various operating conditions and faults as datasets available in practice are often scarce.

3. Computational Resources: Supervised deep learning for dynamic modeling of power electronic systems involves complex computations and thus requires massive amounts of computing power and memory. Optimal management of the hardware resources is a major concern particularly for real time systems.

4. Interpretability and Explainability: One of the significant drawbacks of DNNs is that they are considered as black-box models and it is challenging to the extent or feature that has been used for the model's decision making. Explainability is important in order to gain society's trust and acceptance in areas that require models to be built.

5. Generalization across Different Conditions: It turns out that DNN models trained on particular databases might provide low performance at distinct operational circumstances, which means that they would not generalize at instances when they encounter or work under conditions other than those used in the training process. Therefore, for the improvement of the model's robustness, transfer learning and domain adaption approaches are considered.

6. Integration with Existing Control Strategies: The introduction of DNN based dynamic models in the power electronics based AC control system must also address the issues of compatibility with the existing conventional control mechanisms along with the stable and real time nature of the whole system. The integration challenge consists in avoiding disruption of the planned work that needs to be performed in the new working environment, while not degrading system performance.

7. Handling Edge Cases and Outliers: The issues that can arise in power electronic systems include, outlier situations which maybe rare in occurrence or extreme conditions that may be poorly modeled during training. DNN models require protection techniques to handle such outliers adequately without costing the general prediction performance.

8. Validation and Benchmarking: The validation of the accuracy and usefulness of DNN-based models for dynamic modeling involves real-world datasets and the comparison of the performance with the conventional modeling methods. Another factor that should be defined for a given model is the method for obtaining references for estimating effectiveness and reliability, preferably based on realistic considerations.

Solving these problems is an applied interdisciplinary problem in the machine learning area, power electronics, and control systems, with synergies in the development of better algorithms, data acquisition, and the use of computational tools. The triumphant over these impediments would make the optimal use of the DNNs towards increasing the accurate, efficient, and robust control of the AC power electronic systems in various fields.

4. MAJOR CONSIDERATIONS IN DESIGNING DEEP NEURAL NETWORK BASED DYNAMIC MODELLING METHOD FOR AC POWER ELECTRONIC SYSTEMS

Deciding on the use of deep neural network (DNN) based dynamic modeling methods [30] for AC power electronic systems involves the following considerations to win the approach's implementation and performance battles. Here are five key considerations:

1. Model Architecture Selection: Selecting the proper DNN architecture is important because of AC power electronic systems' complexity and nature. CNN might be necessary for spatial data analysis while RNNs could be needed to handle temporal structures and interdependencies or a combination of CNN, RNN to capture the underlying system dynamics is needed.

2. Data Preprocessing and Augmentation: Cleaning raw data forms part of the important steps in preparing data to feed into models although this increases the preprocessing time. Such factors involves Normalization of data, Scaling of features and managing of Missing data. It also augments

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the training data, thus making the model more robust In addition to that, augmentation techniques, for instance, data synthesis or augmentation through simulation can also enhance model robustness.

3. Training and Optimization Strategies: Optimizing the DNN training typically requires choosing an adequate loss function, optimization algorithm (for example, SGD), and learning rate parameters. Methods such as batch normalization, dropout, and regularization are equally useful in ensuring less overfitting, and hence increased generality to other working conditions.

4. Validation and Testing Protocols: Validating and testing models and being more stringent in the process will help determine how well the models perform of even help in generalizations. Applications of cross-validation and hold-out validation and comparison with other independent data sets or standard benchmarks enables the user to determine the accuracy, precision and validity of the DNN based dynamic models.

5. Real-time Implementation and Deployment: In the case of applying DNN models that are intended for real-time implementation in AC power electronic systems, perspectives such as computational complexity, real-time response, and compatibility with target processors need to be taken into account. Issues like the model inference speed and memory consumption are paramount to the success of an application that requires fast decision-making and control so that it can integrate well with already existing control systems.

Thus, paying specific attention to these considerations allows for designing and applying DNN-based dynamic modeling methods developed by researchers and engineers that promote further improvements in the performance, dependability, and efficiency of AC power electronic systems in diverse operational conditions and intents.

5. METHODOLOGIES

Originally, every component within the AC power electronic system has the duty of converting, conditioning, as well as managing electrical power in accord with certain operational specifications [31]. Efficiency, reliability, and performance of the system are therefore determined by the manner and control of these components to produce unity AC power output to the load or grid.

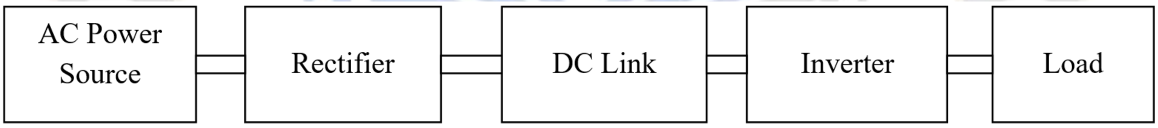

Figure 1. Block diagram for an AC power electronic system

The block diagram of an AC power electronic system may be defined as the representation of devices and components that affect and regulate the AC electrical power. Here's a typical block diagram and an explanation of each component:

1. AC Power Source: This is where the system derives its AC input, most frequently the AC main supply or another AC generator. The input power of voltage, frequency, phase can be wavering and due to this conditioning components may be needed.

2. Rectifier: The rectifier changes the supply power from AC to DC power. This may be using mere diode rectifiers, thyristor-based rectifier such as the controlled rectifiers or even the modern active rectifiers. The type that is to be used depends on the following among others; the voltage level that is desired, the power factor correction that may be necessary and the degree of harmonics to be catered for.

3. DC Link: This link is used to store and also filter the rectified DC voltage that has been obtained from the rectifier. It normally has capacitors for ac ripple removal to ensure that the voltage is stable. The DC link voltage is vital as it acts as a buffer storage point which is middle voltage before the final output.

4. Inverter: The inverter turns the DC power which is at the DC link into AC power of the preferred voltage and both the frequency and waveform. Different topology of inverters can be incorporated using semiconductor devices in form of transistors like: IGBTs, MOSFETs used to switch Direct current voltage to an AC voltage with proper control and thyristors including IGCTs and GTOs. The inverter output can be tied to the utility network in the case of grid-connected systems, or can be optimized to the load (in the case of off-grid systems).

5. Load: The load is the AC power consumer that is produced by the inverter for the convenience of its use. It could be a motor drive, heating element, lighting system or any other electrical device that needs the AC power. This ensures the inverter output conforms with the load expectations with regard to the voltage, frequency, and waveform of the inverter output.

6. Control System: The control system is another and bears the responsibility of monitoring and controlling the AC power electronic system's functions. Some of the typical components are input/output sensors meant for measuring the desired input/output signal, operational amplifiers in feedback loops meant for stability, microcontroller or DSP-based control meant for signal processing and initiation of control signals to the rectifier and inverter. These were control algorithms which promotes effective and optimum functioning as well as supervision of faults in order to protect the components and to be able to function effectively when connected to loads.

5.1. Deep Neural Network (DNN) model for AC Power Electronic System

A general block diagram of the design of a Deep Neural Network (DNN) for the AC power electronic system is drawn in figure 2; the network design used here is originally developed and trained exclusively for AC power electronic system. The following block diagram shows how DNN can be introduced into an AC power electronic system in a systematic manner by applying modern and advanced approaches in machine learning [32] for control, optimization, and/predictive performance.

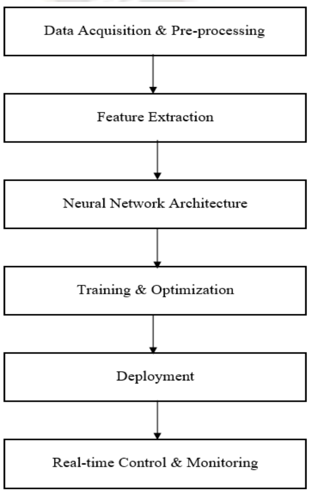

Figure 2. Deep Neural Network (DNN) model for AC Power Electronic System

Each component is explain in detail as follows,

1. Data Acquisition & Preprocessing: In this initial phase, the data collected is from sensors that are included on the AC power electronic system. This data usually incorporates voltage, current, temperature, and other characteristics of the equipment operation. Data cleaning, normalization and feature scaling methodologies are used in this paper so as to present the data in a form that is acceptable by the neural network [33], [34].

2. Feature Extraction: In this phase, features that would be useful for classification are identified from the data pre-processing phase. Feature extraction is very important as it assists in data dimensionality reduction and leads to focus on areas of most importance in training of the neural network.

3. Neural Network Architecture: This component of the Architecture defines the topology of the neural network and how it is implemented. This is made up of' layers of artificial neurons such as the input and hidden neurons and the output layer, activation functions, and interconnection. The architecture is selected depending on the nature of the AC power electronic systems' requirements including accuracy in power prediction, real time control ability and expandability.

4. Training & Optimization: The neural net is employed as a supervised learning which the net is accustomed to previous data or reinforcement learning or unsupervised learning to adjust its parameters weights and/or biases. There are standard minimization techniques such as stochastic gradient descent (SGD), Adam or any other that can be used to reduce the prediction errors and enhance the network's efficiency.

5. Deployment: After it gets trained and optimised a neural network model is incorporated into the AC power electronic system. The process in which software or hardware is incorporated into the model or is retrofitted to it so that it can effectively process data fed into it in real time and provide outputs within the shortest time.

6. Real-time Control & Monitoring: In working, the utilized neural network model is responsible for actual controlling and monitoring processes. This data classification revolves around performing an analysis of data feeds from sensors, arriving at a conclusion, decision or action relative to the data, and feedback probing of the system's performance in looking for signs of abnormality or improvement.

The task of defining an architecture for the Deep Neural Network (DNN) as reflected in figure 3 for an AC power electronic system is to detail the layers and connections from the input to the desired output prediction or control action. The arrows connecting neurons represent the flow of data/information during forward propagation phase and flow of errors during backward propagation phase during training. This DNN architecture is envisioned to maximize system performance, improve speed, and facilitate the changing of control according to the data fed into the AC power electronic system.

i. **Input Layer:** This layer takes input data from the sensors installed in the AC power electronic system. This data commonly consists of voltage, current, temperature, and any other variables applicable during the performance of the operation or task. An input neuron is equivalent to one feature or one data point to be analysed.
ii. **Hidden Layers:** These are layers between the input layer and the output layer and their main function includes carrying out complicated mathematical operation on the data with the aim of deriving features. The parameters which define the structure of the neural network, the number of layers and the number of neurons in each of them, is the choice of the designer depends on the specific problems in question and the amount of available data.

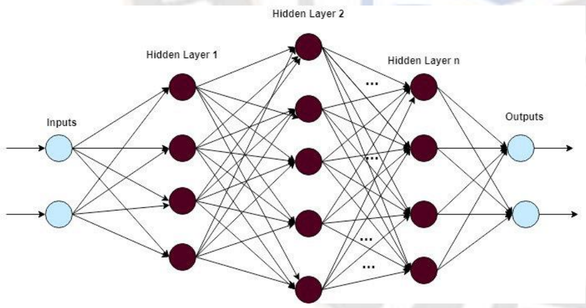

Figure 3. Deep Neural Network (DNN) architecture for AC Power electronic system

iii. **Output Layer:** The final layer or output layer gives the final forecasts or control decisions depending on the information that has passed through the hidden layers. In the case of an AC power electronic system, they could be forecasted parameters which involve control settings for converters (for example, rectifiers or inverters), expected loads, fault analysis results, or any other decisions regarding the system's functionality.

6. CONCLUSIONS

Therefore, this work on deep neural network-based dynamic modeling of AC power electronic systems reveals new directions and possibilities of progress in modeling, controlling, and optimizing these systems. From all the discussed studies, it can be concluded that deep learning approaches such as CNNs, RNNs, and their combinations provide means for efficient modeling and analysis of the power electronic systems characterized by multiple nonlinear dynamics. These models are particularly suitable for estimating transient responses securely, improving the fault-detection performance, and fine-tuning the control schemes in the real-time system environments. Also, the developments in transfer learning, ensemble learning, and knowledge explanation of AI models play a crucial role in optimizing the performance, stability, and explicability of AI-driven solutions essential to solve real-world problems. Nevertheless, the applied research pointed out several difficulties and factors that should be discussed further. These are the issues such as, availability of massive and multiplex data for training models, computational challenges related to deep learning architectures and the issues regarding the explainability of black-box systems especially in safety-critical applications. Such future developments should aim at improving performance of deep neural network implementations, extension of the integration of deep neural models into existing control architectures, and extension of the use of physics-based model merging with data-based models. All in all, the investigated publications confirm that deep neural networks have a great potential for enhancing the performance, dependability, and resilience of AC power electronic systems in smart grids improving future research in renewable energy and electrical vehicles.

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