Developments and Trends in Machine Learning for Electric Machine Drive Control and Monitoring

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Abstract— **The literature on applying machine learning (ML) approaches to the control and monitoring of electric machine drives is methodically summarized in this review paper. The rapid advancement of specialized embedded hardware platforms and learning algorithms is expected to make machine learning (ML)-based data-driven approaches common tools for automated high-performance control and monitoring of electric drives. This article also offers some perspectives on how to encourage its broad implementation in the industry, with an emphasis on ML algorithm deployment on embedded system-on-chip field-programmable gate array devices.**

Keywords— Field-programmable gate arrays (FPGAs), embedded systems, artificial intelligence (AI), deep learning, power electronics, machine learning (ML), and reinforcement learning (RL).

I. Introduction

After the first back propagation paper was published in 1986, the motor control community has been well-informed about the rapid advancements in machine learning (ML) [1]. The work that was done three years later to train an offline neural network to simulate the actions of hysteresis current controllers in a three-phase pulsewidth modulation (PWM) inverter [2] provides clear evidence of this. A number of groundbreaking studies on general voltage-fed ac machines [3], [4], induction machines [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], and [15], dc machines [16], [17], synchronous machines [18], and switching reluctance machines [19] were conducted in the early 1990s in response to this work. In addition to the widespread interest in using machine learning (ML) for motor drive control, these technologies—classification and regression in particular—have also been used in various types of electric machines' condition monitoring and fault diagnosis [20], [21], [22], [23], [24], [25], [26], and [27].Around that time, ML models like emerged, and the field of power electronics began to progressively advance. In power electronics and motor drives, neural networks have emerged as the key field for complicated system identification, control, and estimate [28].

Nevertheless, it was also determined that "industrial applications of neural networks in power electronics appear to be very few at the moment, despite the advancement of technology" [29].

II. Ml Algorithems

A. Supervised Learning

One machine learning job that entails building models to map input and output data is supervised learning. When labeled data is used to train models for classification or regression issues, the process is referred to as "supervised." ANN, support vector machines, and ordinary least squares (OLS) are a few of the most popular supervised learning algorithms. These algorithms have been widely used for the estimation of models or model parameters related to electric machine drives, as well as for the control and monitoring of the drives, as will be covered in following sections.

B. Unsupervised Learning

An algorithm known as unsupervised learning analyzes and interprets data only on the basis of input. Unsupervised learning classic problems include anomaly detection, dimensionality reduction, and clustering. Unsupervised learning methods, in contrast to supervised learning, rely on the data's intrinsic structure to be discovered. Feature engineering for supervised learning can also be applied using unsupervised learning as a supplementary preprocessing step [80].

III. Scope

This article aims to give a thorough review of the literature that uses machine learning approaches to electric machine drives, spanning from the 1980s to the current state of the art. The field of electric machine drives has made extensive use of classical artificial intelligence (AI) techniques, such as expert systems [81], fuzzy logic systems [6], [82], [83], [84], [85], [86], [87], [88], [89], [90], and evolutionary algorithms [83], [91], [92], [93], [94], [95], [96]. However, the authors humbly believe that AI is not used here by definition because standard procedures pale in comparison to the state-of-the-art research in AI computer science.

Additionally, the generated algorithms don't fit the conventional notions of "intelligence," which model "cognitive" abilities like perception, attention, memory, and language processing [97]. Consequently, even though some authors have used the word "AI" in the names of their articles, "machine learning" will be used for the remainder of this article.

IV. Implementing ML-Based Electric Machine Drives In Embedded Systems

A. Brief History Of Embedded Systems For Electric Machine Drives

Additionally, two model reference adaptive speed neural controllers were implemented in [213] and [214] using x86 microcomputers at a sampling rate of just 500 Hz. The low sampling rate of the controllers remained hindered them, even if they were demonstrated to compare favorably against the benchmark PI controllers during transients [214]. Additionally, the authors of the example research in [215] and [216] used a Texas Instruments TMS320C30 DSP to perform the remaining indirect FOC control and an ANN-based current controller.

B. Selecting Appropriate Embedded Systems for Ml-Based Electric Machine Drives

The highest allowable computation time for each control loop is tc = 25 µs to tc = 100 µs. This is because the control frequency for ML-based high-performance electric machine drives is generally in the range of 10–40 kHz, necessitating ultralow latency in the order of microseconds. The available time for the inference of deep neural networks must always be less than a whole control cycle, excluding the time required for ADC sampling, signal scaling/filtering, software-based protection logic, and other tasks. In addition, machine drives will have to communicate with a wide variety of sensor types in order to effectively estimate, regulate, and monitor electric machines for various industrial uses.

C. Implementing Ml-Based Motor Control In Fpgas

A condensed illustration of using an ML-based motor control algorithm on a dual-core reconfigurable SoC is provided in Figure 1.Initially, the measurements are processed by digital filters built into the FPGA after being read from the ADCs. Following that, neural network inference is carried out in

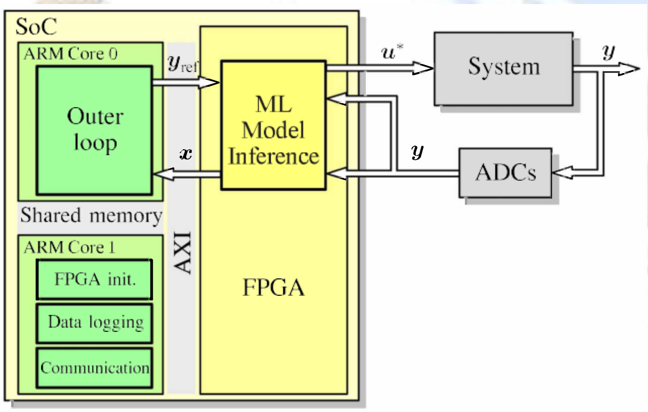

FIGURE 1: SoC construction based on FPGA for machine learning model inference in motor control applications. Taken from [244].

the FPGA in order to calculate the present state x(k). The reference instruction (position, velocity, or torque) yref(k) is provided by an outside control loop operating on ARM Core 0. The integrated advanced extensible interface (AXI) is responsible for implementing the interface between Core 0 and FPGA. Tasks like data logging, interacting with other users and systems, and initializing the FPGA—which includes libraries, tenants, the real-time operating system, drivers, and application programming interfaces—can also be coded into ARM Core 1.

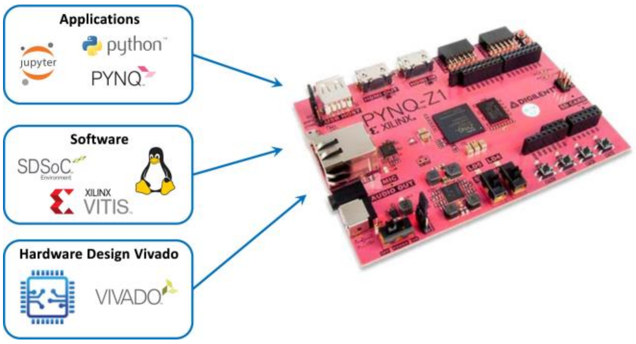

FIGURE 2. Xilinx's open-source PYNQ project offers a foundation for quick prototyping and development together with an intuitive software interface [250].

is enormously complicated [249], and this constraint only gets worse when deploying machine learning algorithms with deep structures and plenty of parameters. into fully optimized parallel hardware designs. Fortunately, there are a number of tools and tailored settings to make this process go more quickly than having to start from scratch. We will demonstrate many possible approaches to using an FPGA-based, trained machine learning controller for electric motors.

I. *Pynq—Python Productivity For Zynq*

By utilizing the Python language and associated libraries, Xilinx's PYNQ open-source initiative seeks to make using Xilinx platforms easier [250]. The PYNQ platform lowers the entrance barrier for individuals with little expertise in hardware design and increases the productivity of designers who are already familiar with Zynq, Zynq UltraScale+, Zynq RFSoC, and Alveo accelerator boards.

II. *Matlab Hdl Coder And Xilinx System Generator (Xsg)*

The programming of Xilinx, Microsemi, and Intel FPGAs may be automated with the help of HDL Coder's workflow adviser [256]. In particular, it can produce over 300 HDL-ready Simulink blocks, MATLAB functions, and Stateflow charts into portable synthesizable Verilog and VHDL code. Programming FPGAs at a high degree of abstraction for machine learning (ML)-based motor control applications is possible using HDL Coder. The resulting HDL code can be imported and compiled into customized intellectual property (IP) cores using Xilinx Vivado Design Suite or Intel Quartus.

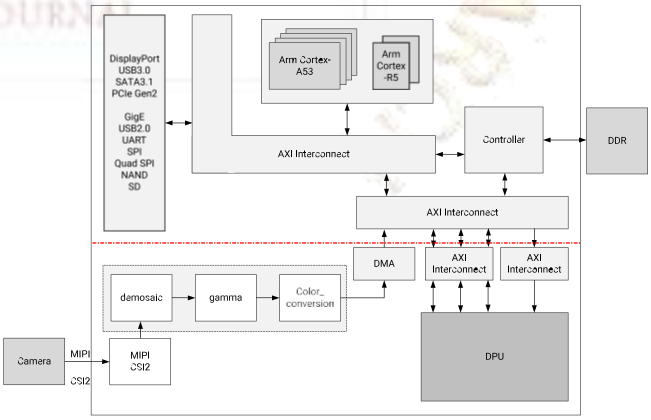

FIGURE 03:A system with an integrated DPU is shown in [258].

High-level integration of different IP blocks made with the MATLAB/Simulink graphical interface is provided, along with description languages like Verilog and VHDL. Furthermore, the Simulink toolkit makes debugging and testing of HDL designs simple and adaptable. When compared to skilled FPGA designers, these toolboxes' performance and resource use could not produce the best design.

III. *Deep Learning Processor Unit (Dpu)*

Along with its high-level synthesis (HLS) tool, which assembles deep learning C/C++ code for PL in the hardware, Xilinx has also built the DPU IP core [257]. With direct connections to the PS, the DPU may be implemented into the PL of certain Zynq-7000 SoC, Zynq UltraScale+ MPSoC, and Versal AI edge devices. This DPU, which consists of the register configuration module, data controller module, and convolution computation module, is specifically a programmable engine designed for CNNs.

It should be mentioned, nonetheless, that Lillicrap et al. [259] analyze picture data where CNNs excel since they learn from raw pixels. As was previously mentioned, electric machine drives handle data using a whole different data format than CNNs. Given the high cost of computation, it is unknown how well CNNs will work with low-cost embedded systems like FPGAs for low-dimensional control tasks, such as electric motors. However, we can still make use of this DPU IP core if CNNs are chosen to perform certain motor control tasks by utilizing its included convolutional layers and combining them with additional neural network layers created in bespoke IP cores.

or “Magnetization {A[m(1)]}”, not just “A/m”. Do not label axes with a ratio of quantities and units. For example, write “Temperature (K)”, not “Temperature/K”.

Acknowledgment

An extensive assessment of the most recent state-of-the-art machine learning systems for electric drive management and monitoring is given in this article. Future study must address some of the outstanding concerns that remain despite the ongoing growth of pertinent publications in this sector.

A. *Developmental Endeavor*

Even while FPGAs can provide improved connection, flexibility, and energy economy, one of the main drawbacks of utilizing FPGAs is the technical work necessary for creation. Developing FPGAs necessitates both software engineering and hardware configuration expertise, in contrast to developing GPUs, which solely requires software engineering expertise. Even for experienced FPGA engineers, manual design techniques are particularly time-consuming due to the complexity of implementing ML models on FPGAs.

To allow fast and effective training of RL control on FPGAs, therefore, an automated design workflow from the RL's neural network architecture to the hardware design is required (i.e., not just for policy inference but also for online policy learning). Without requiring in-depth understanding of hardware design, researchers and engineers may swiftly construct a variety of machine learning models for motor control applications by developing an efficient automated design approach.

B. *The application's exertion*

Because machine learning is data-hungry, it usually requires expensive and time-consuming individual test bench training for every drive system. Therefore, for industrial mass production utilization, the ability to quickly transfer an ML approach between multiple applications is a problem. It is possible to address this problem from a hardware and software standpoint. Certain machine learning algorithms are specifically created to facilitate transfer learning with robust domain adaption capabilities in software words. Furthermore, an HIL environment may simulate the hardware platform of many electric drive systems, which facilitates the collection of sufficient simulated data for the training of machine learning models for any industrial application.

C. *Security*

As machine learning is inherently stochastic, its output need to be regarded as stochastic as well. Consequently, an ML model's intrinsic chance of failure might lead to issues if an ML approach generates outliers for control or estimating purposes. Therefore, adverse effects on mechatronic systems' behaviors might jeopardize their chances in applications where safety is crucial.

D. *Readability*

ML models are extremely intricate and challenging to comprehend or describe. As mentioned in [227], for example, a new machine learning model suggested for electric motor applications may have almost 10,000 parameters. Furthermore, millions or billions of parameters may be present in commercially available machine learning models used for tasks like image identification or natural language processing. While inter- pretability alone cannot ensure safety, it is essential for tracking functional safety and identifying model failure points. Therefore, before ML models are commercially used in driving applications, more thorough research into their interpretability and explain ability is required.

It is expected that the ML-based data-driven control and monitoring schemes would be able to give unmatched performance in terms of quick exploration and domain adaptation after many of the practical challenges outlined above have been resolved. As a result, they have a strong chance of replacing current electric machine drive technology with next-generation low-cost microcontrollers now employ model-driven techniques.

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