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Operating Characteristics and Optimization Strategies for a Machine Learning-Based Buck Converter

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Abstract. This paper investigates the application of machine learning in analyzing the operating characteristics of buck converters. Addressing the practical challenges in traditional power electronics design—such as the reliance on human expertise and limited model fitting performance under complex operating conditions—it systematically reviews three mainstream research approaches: artificial intelligence (AI) assisted circuit parameter design, machine learning-based output voltage prediction, and scientific machine learning (SciML) for parameter prediction that integrates physical mechanisms. This paper analyzes the processes of different types of technologies and compares performance of different algorithms in modeling tasks. The findings indicate that existing solutions commonly have practical limitations, including high dependence on simulation data, insufficient hardware validation, incomplete engineering evaluation metrics, and lack of multi-condition testing scenarios. Regarding the shortcomings mentioned above, this paper proposes multiple optimization approaches, including integrating simulated and measured datasets, expanding test conditions, incorporating engineering constraints such as losses and temperature, and addressing model inference delays, to provide references for future research on DC-DC converters with machine learning.

Keywords: Machine learning; buck converter; circuit parameter design.

1. Introduction

Recently, as the new energy power grid technology develops, the operating conditions of Buck converters are becoming increasingly complex, so many researchers have gradually introduced machine learning methods into their applications [1]. The application of machine learning to Buck converters can achieve intelligent optimization of circuit parameters and rapid prediction of characteristics, and adaptively adjust control parameters to enhance system disturbance rejection capability. Scientific machine learning integrates circuit physical mechanisms, compensating for the poor generalization of purely data-driven models, and provides new research ideas for DC-DC converters [2].

Currently, many researchers are gradually introducing reinforcement learning into the field of converter control. At this stage, there are studies that use the Q-learning algorithm to optimize the proportional-integral-derivative (PID) control parameters of Buck converters, achieving real-time adaptive adjustment through data-driven methods, which effectively improves voltage regulation accuracy and dynamic disturbance rejection capability, indicating that machine learning has been preliminarily applied to the intelligent control optimization of Buck converters. However, current research in this area mostly focuses on controller parameter tuning and has not yet extended to converter characteristic prediction and circuit parameter optimization [3]. Patil et al. developed a machine learning-assisted fuzzy system to monitor the health condition of in-service high voltage direct current (HVDC) converter transformers, achieving up to 96.64% accuracy in health classification [4]. Kamalesh et al. designed a machine learning algorithm to achieve mode selection and control of a multi-port DC-DC converter, and completed verification through hardware-in-the-loop simulation combined with physical experiments [5]. Elma et al. used a machine learning algorithm to achieve high-precision estimation of on-chip magnetic core coupled inductor parameters, and constructed an optimization framework to complete the design of an interleaved Buck converter, with simulation verifying that the scheme can improve operating efficiency [6]. Zhao et al. proposed

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a parameter estimation method for Buck converters based on physics-informed machine learning, integrating deep neural networks with circuit physical models, and relying on limited datasets to achieve high-precision estimation of multiple device parameters, providing new ideas for the application of machine learning in power electronics scenarios [7].

However, most current studies still have shortcomings, such as research on a single aspect and the use of only simulation platforms without actual hardware implementation. Therefore, this paper analyzes and studies the cases of machine learning applications in Buck converters, and proposes some optimization ideas for them.

2. The Research on Buck Converters

2.1. AI-D for Circuit Parameters of Power Converters

Li et al. proposed a parameter design scheme based on artificial intelligence for the circuit parameter design problem of power converters [8]. The design of parameters is very important for ensuring the performance and operation of power converters. Current parameter design methods include manual design and computer-aided optimization (CAO) methods. Among them, traditional manual design relies on experience and requires a large number of trial calculations, which not only leads to a heavy workload but also results in low design accuracy. Even with computer-aided optimization methods such as genetic algorithms, there are still drawbacks of consuming a great deal of time and effort. This paper introduces artificial intelligence technology based on neural networks, utilizing its ability to fit complex nonlinear functions to achieve automated optimization in the analysis and derivation process. This artificial intelligence-based detection (AI-D) design method combines simulation tools and genetic algorithms to complete the optimization of parameter design, and takes a Buck converter as an example for the design, with verification completed in the circuit parameter design of a synchronous Buck converter for a 48V-to-12V auxiliary power supply system in electric vehicles. The design example takes efficiency optimization as the objective, while also considering multiple constraints including volume, voltage ripple, and current ripple. Finally, the feasibility and accuracy of this method were verified through hardware experiments.

2.2. Voltage Prediction by Using Machine Learning

Kovalevas et al. conducted modeling and comparative experiments using multiple decision tree machine learning algorithms for the prediction of the output voltage of Buck converters [9]. Machine learning, as a branch of artificial intelligence, enables systems to autonomously learn patterns from data, reducing manual workload. On the WEKA platform, four decision tree algorithms—PERTree, M5P, RandomTree, and RandomForest—were used for dataset classification. The database was first converted into the ARFF format required by the software, and then model training was completed. The article also verified the feasibility of using machine learning to predict the electrical characteristics of converters.

2.3. Apply Machine Learning to Power Electronic Parameter Prediction

Harison et al. proposed a hybrid scientific machine learning (SciML) method that combines physical models with machine learning for the parameter prediction problem of power electronics systems, and used a Buck converter as the simulation verification object to achieve circuit output prediction, which is highly consistent with this topic—the use of machine learning to analyze the operating characteristics of Buck converters [10]. This method can reduce the requirement of pure machine learning for dataset size, shorten training time, and simultaneously reduce the computational overhead of traditional physical models. The simulation application results carried out on a Buck converter show that, compared with models without physical mechanism assistance, this new method can generate prediction results with higher accuracy in a shorter time.

Based on the above, the following Fig. 1 presents the main core points and main research points of the above research work.

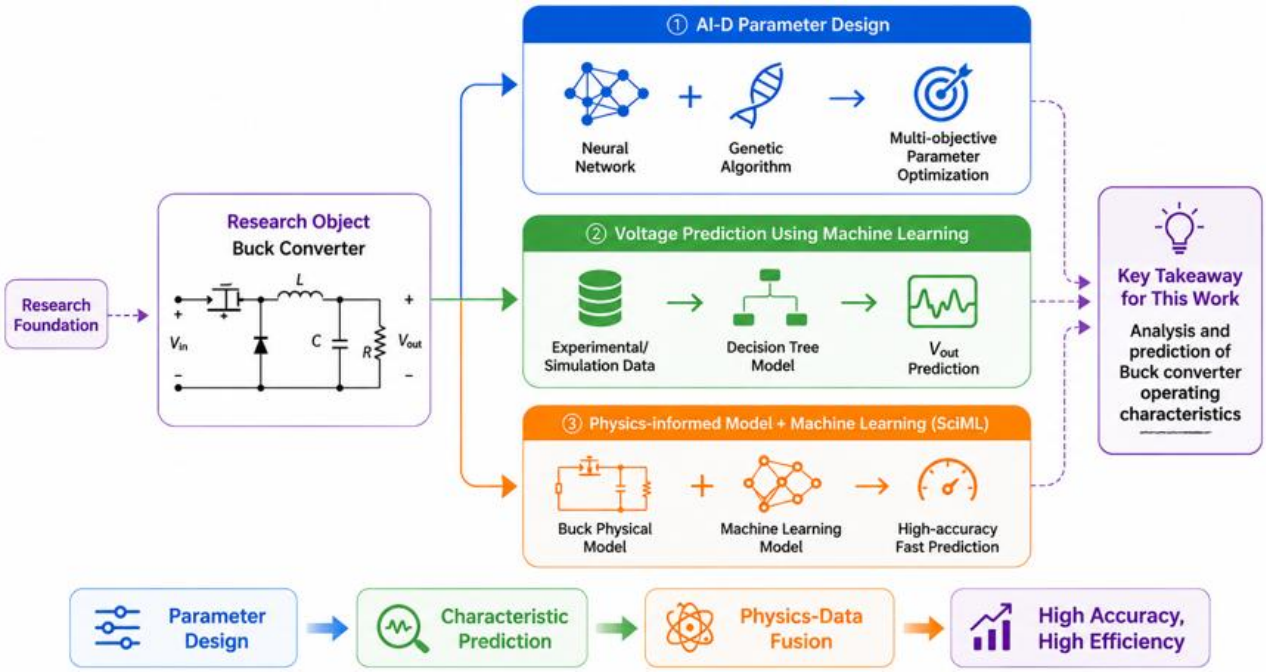

Fig. 1 Schematic diagram of the core points and main research points of related research works. (Picture credit : Original)

3. Limitation Analysis and Solutions

3.1. Shortcomings and Optimization Directions of AI-D Design

Li et al. validated the AI-D parameter design scheme using the case of a 48V-to-12V synchronous Buck converter for electric vehicles as an example. Although verification results were obtained, other conditions were not tested, and the input voltage and load fluctuation conditions were not varied over a wide range. The generalizability of the algorithm was not fully demonstrated, and the effectiveness of the model when applied to other converters cannot be known. Secondly, this paper only considered volume, voltage ripple, and current ripple, while lacking engineering key indicators such as device losses, thermal performance, electromagnetic interference, and cost. Real-world power electronics design requires trade-offs between cost and heat generation, but this model did not incorporate them. Thirdly, all the data for the neural network came from simulation tools rather than a large amount of data collected from actual hardware experiments. The use of simulation tools leads to the neglect of actual parasitic parameters and component tolerances in real devices, and the deviation between real hardware and simulation can cause the neural network model to suffer from accuracy degradation in physical scenarios.

In response to the above issues, this paper gives the following optimization suggestions: First, in subsequent research, this AI-D model framework can be tested on Buck converters in other applications, expand the scope of testing, and set up multiple groups of input voltages and dynamic loads to verify the stability of this algorithm under varying operating conditions. Furthermore, a large amount of hardware measured data can be added to the training set, incorporating data such as parasitic parameters of components and device tolerances into the dataset, so as to reduce the model prediction deviation caused by simulation idealization and improve the prediction accuracy of the neural network when facing real hardware. The optimization objectives can be augmented with power losses, device temperature, material cost to achieve multi-dimensional trade-offs, so that the output parameter schemes are closer to actual product development.

3.2. Restrictions and Directions of Optimization of the Voltage Prediction Method

Kocaleva et al. used multiple machine learning methods to predict the output voltage of converters. However, their method has some drawbacks: They just adopted the decision tree type algorithm to predict the output voltage, and other mainstream algorithms were not introduced; they did not compare the difference between various algorithms. This coverage of algorithm selection was restricted, so it was not possible to draw any comprehensive conclusions. Second, all the experiments were conducted in the WEKA simulation platform for training and testing the models and the actual measured data were not collected from hardware circuits. The simulation environment is idealized, where practical interferences like real circuit noise and parameter drift of devices are neglected, and generalization ability of the model on real hardware has not been tested by physical experiments. Third, the study mainly looked into the prediction of one electrical quantity, namely the output voltage, without being expanded to any other significant quantities of the Buck converter such as efficiency or ripple, which gives a relatively small research scope.

To cope with the above issues, this paper provides the following optimization suggestions: In the future research, the algorithm pool can be increased to include model types like neural networks and the prediction accuracy and calculation cost of various types of algorithms can be compared to select the prediction model most suitable for the Buck converter scenario. In addition, in the experiments, an actual Buck hardware experimental platform can be established to obtain real circuit data in various circumstances, and the simulation data set and hardware measured data set can be used together for training and testing, to enhance the model's generalization performance on real devices. Lastly, it is proposed that the research can be extended to predict other operating characteristics of Buck converters, such that the output indicators predicted are not limited to output voltage, but include other important output characteristics such as efficiency and ripple current, and the range of input voltage and load can be extended to test the prediction performance of the model under multiple operating conditions.

3.3. Deficiencies and Directions for Optimization of SciML in Power Parameter Prediction

Harison et al. have successfully proposed a method which combines physical models with machine learning to predict parameters of power electronic systems, however, it still has some drawbacks. First, it is still the old problem that the study did not test anything physically, just simulated the results. The results of all experiments were carried out using the Buck converter simulation without testing on a real hardware platform. Secondly, the evaluation method is oriented to the theoretical prediction and it does not contain engineering performance indicators. The article only considers the accuracy of the prediction of system output, but does not introduce the important parameters of power electronics engineering, such as the efficiency of the converter, the loss of the device, the temperature rise of the device, etc., into the model and evaluation system, which is still lacking in actual engineering application. Third, the paper didn't mention the cost of training the models, nor the performance of running them in real time. The paper only compared the training time, but not the model inference time, with purely data-driven models. For many power electronics scenarios, the real-time prediction is required and if the model inference latency is high, it cannot be used directly for real-time control. Original paper does not analyze the speed of inferences and the utilization of computational resources.

Based on the above problems, this paper has the following optimization suggestions: First, in the next study, it is possible to build a real hardware experimental platform, and get the circuit actual data of various conditions, then combine the simulation data and measured data to get the more complete experimental conclusions, which is closer to the practical situation. Second, the research shows that, other than the output prediction, various engineering indicators like circuit efficiency, device losses and temperature can also be integrated into the model prediction and evaluation criteria, giving the method a more practical engineering value and making it more real. Finally, apart from training, inference latency, memory usage and computational overhead should be added as evaluation metrics;

and the network should be lightly optimized for real-time control application to satisfy the requirement of the power electronics real-time system

Table 1 provides the key points in these three common research studies. It shows what is limited in the paper and what can be improved to better understand the analyses above.

Table 1. The main limitations of the three research works and the corresponding solutions.

Study	Key Limitations	Suggested Improvements
AI-D Parameter Design	• Limited converter types and operating conditions. • Incomplete engineering objectives. • Heavy reliance on simulation data.	• Multi-converter and multi-condition validation. • Multi-objective optimization including loss, temperature, cost, and EMI. • Integration of hardware measurements and component nonidealities.
Output Voltage Prediction	• Limited algorithm diversity. • Lack of hardware-based validation. • Single prediction target.	• Comparison of diverse models. • Hybrid simulation–experimental datasets. • Prediction of voltage, efficiency, ripple, and other key characteristics.
SciML-based Parameter Prediction	• Simulation-only validation. • Limited engineering metrics. • Insufficient computational-performance analysis.	• Hardware-assisted model validation. • Inclusion of efficiency, loss, and thermal metrics. • Evaluation of inference latency, memory usage, and computational cost.

4. Conclusion

This paper reviews the relevant research on machine learning in the optimization and analysis of Buck converters, identifies the shortcomings of existing methods, and draws the following conclusions:

First, AI-D-based converter parameter design mostly relies on simulation data for research, and there is a gap from real hardware operating conditions. For better practical implementation, it is not sufficient to only perform simulations; it is necessary to incorporate test data from actual circuits, take into account real engineering factors such as losses and temperature, and verify the actual performance of the model under different operating conditions.

Second, at the current stage, much of the machine learning-based prediction and analysis for Buck converters only focuses on output voltage, with less attention paid to practical characteristics such as efficiency and ripple. Subsequent research can try more algorithmic models, combine data from both simulation and physical acquisition, and establish more comprehensive evaluation criteria.

Third, although SciML scientific machine learning incorporates circuit physical mechanisms, most work still remains at the simulation stage, lacking hardware experimental support, and rarely considers model operating speed and computational burden. If it is to be used in actual power electronics control scenarios, it is still necessary to rely on hardware platforms for verification, perform lightweight processing on the model, and adapt it to the requirements of real-time operation.

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