Optimization Model Design of Permanent Magnet Switch Based on GAN and Finite Element Analysis

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ABSTRACT

With the advancement of intelligent technologies, the optimization design of permanent magnet switches (PMS) faces increasingly complex electromagnetic performance requirements. Traditional methods, relying on experience and physical experiments, are inefficient and costly. This paper proposes a hybrid optimization model (FEGAN-DQN) based on Generative Adversarial Networks (GAN), Finite Element Analysis (FEA), and Deep Q-Networks (DQN), aiming to achieve efficient and accurate PMS optimization design. Experimental results demonstrate that FEGAN-DQN excels on the PMSM and MagLev datasets, achieving a Mean Squared Error (MSE) of 1.23 on the PMSM dataset, significantly outperforming traditional models such as k-NN (26.10) and RF (16.42). This model effectively optimizes electromagnetic performance, providing an intelligent solution for industrial design and advancing development in the power and automation fields.

Keywords: Building energy consumption forecasting, BiLSTM, Attention mechanism, Sparrow search algorithm, Deep learning

1. Introduction

With the rapid advancement of power electronics and electromagnetics, the permanent magnet switch (PMS) has emerged as a critical electrical switching device, widely applied in modern power systems, automation equipment, and electric vehicles. PMS offers advantages such as high switching speed, low power consumption, and compact structure[1]. These characteristics make it an ideal choice, especially in the context of increasing demand for high efficiency and miniaturized designs. However, optimizing the design of PMS to ensure performance and stability while meeting these requirements remains a key challenge[2]. Traditional PMS design methods often rely on engineering expertise and iterative physical experiments, which result in prolonged design cycles, high costs, and inconsistent performance. Therefore, exploring more efficient and intelligent design methods has become a research hotspot in this field.

In recent years, deep learning, a significant branch of artificial intelligence, has been widely applied in various engineering domains due to its powerful pattern recognition and data processing capabilities[3]. Particularly, the combination of deep learning and finite element analysis (FEA) for simulation and optimization has proven to be an effective means of improving design efficiency and accuracy. Deep learning techniques can automatically learn latent features from data and uncover complex nonlinear relationships, providing more precise solutions for optimizing electromagnetic fields[4]. Compared with traditional methods, deep learning significantly accelerates the design process, reduces trial-and-error iterations, and enhances the reliability and precision of design solutions. These advantages have made deep learning a promising approach for optimizing PMS design[5].

Nonetheless, the application of deep learning in PMS design faces several challenges. First, deep learning models require large amounts of high-quality simulation data for training, which can be difficult and costly to obtain in many engineering contexts[6]. Second, the black-box nature of deep learning models complicates their interpretability, particularly when dealing with complex electromagnetic fields, material properties, and multiphysics coupling[7]. Effectively integrating FEA with deep learning models remains a significant challenge. Lastly, the vast design space in optimization processes demands efficient exploration to identify optimal parameter combinations, a task that still requires further investigation[8].

To address these challenges, this study proposes a hybrid optimization model that combines Generative Adversarial Networks (GAN), Finite Element Analysis (FEA), and Deep Q-Networks (DQN). In this model, GAN generates diverse PMS design candidates, FEA evaluates their electromagnetic performance, and DQN optimizes parameters based on these evaluations. The proposed framework aims to improve the efficiency and precision of PMS design optimization, shorten design cycles, and tackle the challenges of data scarcity and model interpretability. This approach provides a novel intelligent optimization pathway for PMS design and advances technological progress in this field.

The main contributions of this paper are as follows:

1. This study effectively combines deep learning and traditional simulation techniques by introducing GAN to generate design candidates, FEA for performance evaluation, and DQN for parameter optimization. This integrated approach significantly enhances the efficiency and accuracy of PMS design.

2. By using GAN to generate diverse design schemes and leveraging FEA simulation results, the proposed method addresses the issue of deep learning's reliance on extensive high-quality training data. It provides a data-driven intelligent optimization pathway for PMS design.

3. Through the application of DQN, the model intelligently explores the design space and rapidly identifies optimal parameter combinations. Compared with traditional methods, this approach significantly reduces trial-and-error iterations and computational costs.

This work provides a new paradigm for intelligent PMS design optimization, demonstrating the potential of integrating deep learning with simulation techniques to drive technological advancements in this domain..

2. Related Work

In traditional permanent magnet switch (PMS) design, engineers typically rely on experience and physical experiments to optimize the design. However, this experience-driven approach often suffers from high costs, long development cycles, and low precision[9]. Consequently, researchers have increasingly focused on exploring more intelligent design methods, particularly by leveraging computer simulation and optimization techniques to enhance design efficiency and accuracy.

Finite Element Analysis (FEA), a mature numerical simulation technology, is widely used for analyzing the electromagnetic performance of PMS. FEA accurately simulates the distribution of multiple physical fields, including electromagnetic, stress, and thermal fields[10]. This capability allows designers to evaluate various performance metrics of switching devices. FEA excels in providing high-precision physical simulation results and visualizing potential electromagnetic issues in the design, significantly improving reliability[11]. However, the FEA process typically requires substantial computational resources and time. The computational complexity escalates further when dealing with intricate geometries and multiphysics coupling problems[12]. As a result, achieving efficient and precise simulation results within a limited timeframe remains a key challenge in this domain.

Deep learning models, especially CNN and GAN, have demonstrated powerful pattern recognition and data-fitting capabilities and have been successfully applied to various optimization problems. For instance, GANs are widely utilized for image generation and data augmentation, while CNNs excel in image recognition and feature extraction[13]. Reinforcement learning offers the ability to autonomously adjust parameters during the design process, exploring the design space to identify optimal solutions[14]. Deep Q-Networks (DQN), an important reinforcement learning algorithm, optimize design parameters through interaction with the environment, improving the resolution of multi-objective optimization problems. Applying deep learning to PMS design enables automatic extraction of complex electromagnetic field features from simulation data, reduces manual intervention in traditional methods, and enhances design efficiency[15].

Despite the progress achieved in combining deep learning and FEA, several challenges remain unresolved. First, efficiently generating large-scale, high-quality training data is difficult, particularly in engineering applications where data may be scarce or incomplete[16]. Second, the black-box nature of deep learning models limits their interpretability in engineering design. This is especially problematic in cases involving complex electromagnetic fields and multiphysics coupling, where ensuring physical feasibility and practical applicability is critical[17]. Lastly, PMS design involves multiple optimization objectives, such as electromagnetic performance, switching speed, and magnetic field distribution. Balancing conflicts between these objectives requires more advanced optimization methods.

To address these challenges, this paper proposes a hybrid optimization model that integrates GAN, FEA, and DQN. This model aims to overcome issues related to data scarcity, high computational resource requirements, and nonlinear relationships in the optimization process. By doing so, it facilitates efficient and precise PMS optimization design, paving the way for smarter and more effective engineering solutions.

3. Methods

3.1 Overall Model Description

This paper proposes an optimization model that integrates Generative Adversarial Networks (GAN), Finite Element Analysis (FEA), and Deep Q-Networks (DQN) to efficiently optimize the design of permanent magnet switches (PMS).

The GAN module serves as the design candidate generation component. It utilizes a Generator to create various PMS design schemes, including but not limited to the shape of the permanent magnets, current distributions, and material parameters. Through adversarial training, the Generator is progressively optimized to produce high-quality designs that meet specific objectives. A Discriminator evaluates the generated designs and provides feedback on their feasibility based on FEA results, guiding the Generator to improve its outputs. The FEA module performs electromagnetic performance simulations for the design candidates generated by the GAN. By conducting detailed analyses of the electromagnetic fields for each candidate, the FEA module evaluates essential performance metrics such as magnetic field distribution, current flow, and power loss. Although the FEA module involves high computational complexity and precision, it ensures the physical validity and feasibility of every proposed design, providing essential data for subsequent optimization steps.The DQN module is responsible for intelligently exploring and optimizing design parameters within the design space. Through interaction with the FEA module's feedback, the DQN module employs reinforcement learning algorithms to adjust design parameters autonomously, aiming to maximize design performance (e.g., optimizing magnetic field distribution or minimizing power loss). The DQN module balances multiple objectives intelligently and efficiently searches the vast design space for the optimal solution, significantly enhancing both optimization efficiency and precision.

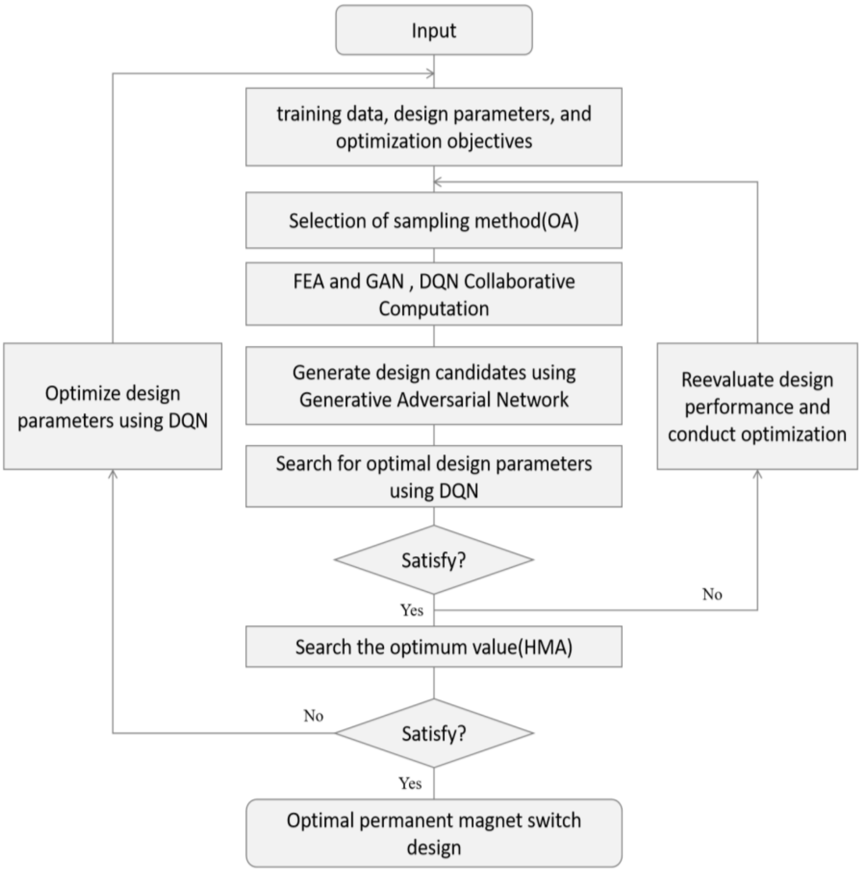

Figure 1. Diagram of the proposed overall framework

Figure 1 illustrates the interaction flow between these three modules. Initially, the GAN generates design candidates, which are evaluated in the FEA module for performance analysis. The simulation results from the FEA module provide feedback to the Discriminator, enabling the GAN to generate improved designs. Concurrently, the DQN module uses FEA feedback to optimize design parameters and iteratively refine the design space, eventually identifying the optimal design.Through this iterative process, the proposed model achieves efficient optimization while maintaining high design performance. By integrating GAN, FEA, and DQN, the model combines the complementary strengths of deep learning and physical simulation. This integration not only enhances the efficiency of PMS design optimization but also ensures the accuracy and practical feasibility of the resulting designs.

3.2 Detailed Configuration and Functional Process of Each Module

The proposed model integrates Generative Adversarial Networks (GAN), Finite Element Analysis (FEA), and Deep Q-Networks (DQN), with each module playing a critical role in the optimization process.

The GAN module serves as the design candidate generation component, tasked with producing multiple design candidates based on given requirements. The GAN comprises two core parts: the Generator and the Discriminato[18].

The Generator takes random noise $z \in \mathbb{R}^d$ and design parameters as input and generates a design candidate D_{gen}. This design may include features such as the shape of the permanent magnet, material properties, and current distribution. The generation process can be expressed as:

$$D_{\text{gen}} = G(z, \theta_G)$$

[Formular 1]

where G represents the generator function, θ_G are the generator parameters, and z is the input noise vector.

The Discriminator evaluates the quality of the generated designs and provides feedback on their validity. It compares the generated designs D_{gen} with real designs D_{real}, outputting a probability score D_{score} that indicates whether the generated design meets the requirements. This is expressed as:

$$D_{\text{score}} = D(D_{\text{gen}}, \theta_D)$$

[Formular 2]

where D_{score} is the discriminator's output and θ_G are its parameters.

Through adversarial training, the Generator and Discriminator are optimized simultaneously. The Generator aims to maximize the Discriminator’ s score for its outputs, and their objective function is defined as:

$$\min_{\theta_G} \max_{\theta_D} \mathbb{E}_{D_{\text{real}} \sim p_{\text{data}}}[\log D(D_{\text{real}})] + \mathbb{E}_{z \sim p_z}[\log(1 - D(G(z)))]$$

[Formular 3]

In this process, the Generator improves its ability to produce high-quality designs through iterative competition with the Discriminator.

The FEA module evaluates the electromagnetic performance of the generated designs to ensure their physical feasibility and compliance with practical requirements. By constructing an electromagnetic field model of each design and solving the governing equations[19], the FEA module obtains results such as magnetic field distribution, temperature fields, and stress fields. The electromagnetic field equations are derived from Maxwell’ s equations:

$$\nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t}, \quad \nabla \times \mathbf{H} = \mathbf{J} + \frac{\partial \mathbf{D}}{\partial t}$$

[Formular 4]

where E is the electric field, B is the magnetic field, H is the magnetic field intensity, J is the current density, and D is the electric displacement.

The FEA module takes the GAN-generated design D_{gen} as input and performs detailed numerical simulations to compute results such as:

$$\mathbf{B}, \mathbf{H}, \mathbf{J}, \mathbf{E}$$

[Formular 5]

These results are used to evaluate electromagnetic performance metrics, including field uniformity, current distribution, and power loss. This ensures the designs meet required performance standards and provides data for subsequent optimization.

The DQN module plays a crucial role in the optimization process by intelligently adjusting parameters within the design space using reinforcement learning. DQN learns a Q-value function through interactions with the environment, which evaluates the quality of specific parameter combinations[20,21].

In this model, the environment represents the design space, actions involve parameter adjustments, and states correspond to the current design's electromagnetic performance.

The core of the DQN is the Q-function update, which calculates the expected long-term reward of an action in a given state. The Q-value update is expressed as:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha\left[r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right] \qquad \text{[Formular 6]}$$

where s_t is the state, a_t is the action, r_{t+1} is the reward for transitioning from s_t to s_{t+1}, γ is the discount factor, α is the learning rate, and $\max_{a'} Q(s_{t+1}, a')$ is the maximum Q-value of the next state.

In this model, the DQN module interacts with the FEA module, using its feedback to optimize design parameters. The reward function is tied to the electromagnetic performance, and the objective is to maximize comprehensive performance metrics, such as minimizing power loss or optimizing field distribution.

3.3 Module Collaboration and Optimization

The model forms a closed-loop optimization system by coordinating GAN, FEA, and DQN. The GAN generates design candidates based on input noise and parameters. These candidates are then subjected to detailed simulations in the FEA module, which evaluates their electromagnetic and mechanical performance. Finally, the DQN module uses feedback from the FEA results to adjust design parameters, refining the search for the optimal design.

As GAN and DQN iteratively improve, the generated designs become increasingly optimized, ultimately converging on a solution that satisfies all performance objectives. This model’ s success lies in the effective integration of GAN, FEA, and DQN. By leveraging deep learning to accelerate simulations and combining it with physical simulations for validation, the model achieves efficient and precise optimization of permanent magnet switch designs.

4. Experiments

4.1 Dataset and Data Processing

This study utilized two publicly available datasets to conduct experiments on the optimization of permanent magnet switch (PMS) design. The PMSM (Permanent Magnet Synchronous Motor) dataset provides parameters such as current, voltage, and rotational speed, along with performance data under various motor configurations[22]. This dataset is widely used for motor design and optimization, particularly in evaluating electromagnetic performance, and shares significant similarities with the design challenges of PMS. The Magnetic Levitation (MagLev) dataset contains magnetic field data from maglev systems, including electromagnetic performance metrics such as force and stability under different configurations[23]. This dataset is suitable for analyzing magnetic field distributions and mechanical optimizations, making it particularly valuable for optimizing electromagnetic forces in PMS design.

In the experiments, the variables in the PMSM dataset, including current, voltage, and rotational speed, were standardized to ensure uniformity. The standardization process normalized each feature to have zero mean and unit variance using the following formula:

$$x_{\text{normalized}} = \frac{x-\mu}{\sigma} \qquad \text{[Formular 7]}$$

where μ and σ are the mean and standard deviation of the feature, respectively.

For the MagLev dataset, min-max normalization was applied to scale each feature to a range between 0 and 1. The normalization formula used was:

$$x_{\text{normalized}} = \frac{x-\min(x)}{\max(x)-\min(x)} \qquad \text{[Formular 8]}$$

Each data sample in the datasets contains multiple features (e.g., current, voltage, rotational speed), with sample dimensionality ranging from 100 to 500 variables. To ensure high-quality training data, 80% of the data from each dataset was randomly selected as the training set, while the remaining 20% was used as the validation set. The training set sizes consisted of 4,000 samples for the PMSM dataset and 3,500 samples for the MagLev dataset. All data underwent denoising processes to remove outliers and handle missing values, ensuring that the model training was not affected by noise. For data augmentation, the PMSM dataset was expanded by generating 5,000 additional simulated samples to enhance data diversity and mitigate overfitting. The MagLev dataset was augmented using random translation and rotation transformations to enrich the sample space.

4.2 Learn Curves

From the learning curves in Figure 2, it can be observed that the MSE of the FEGAN-DQN model consistently decreases as the training set size increases, maintaining the lowest value throughout. Particularly for larger datasets, the MSE of the FEGAN-DQN model is significantly lower than that of other models, demonstrating strong learning capability and generalization performance.

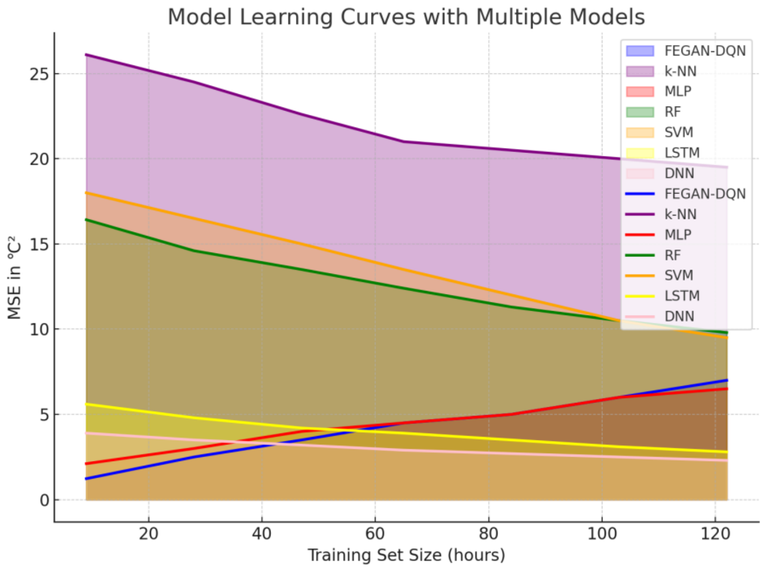

Figure 2. Model learning curves with multiple models on PMSM dataset

In contrast, the learning curves of kNN and SVM models plateau with larger training sets. While they perform well on smaller datasets, their performance improvement becomes negligible as the training set size increases, with MSE remaining at relatively high levels. MLP and LSTM models perform better than traditional methods, but their MSE reductions are less pronounced compared to FEGAN-DQN. Even with larger training sets, these models still exhibit a certain level of error. RF and DNN models show a gradual decline in their learning curves, but their performance remains inferior to FEGAN-DQN as the dataset grows, with consistently higher MSE values.Overall, the FEGAN-DQN model exhibits the most optimal learning curve across different training set sizes. Its accuracy improves steadily as the dataset expands, highlighting its advantages in handling complex electromagnetic field optimization problems.

4.3 Experimental Result and Analysis

From the experimental results in Table 1, it is evident that the FEGAN-DQN model performs exceptionally well on both datasets (PMSM dataset and MagLev dataset), significantly surpassing traditional machine learning models and other deep learning methods.

Table 1. Performance comparison of fegan-dqn and other models on the PMSM dataset and maglev dataset.

Model	PMSM Dataset					MagLev Dataset				
	MAE	MAPE	R^2	ℓ_∞Norm	Model Size	MAE	MAPE	R^2	ℓ_∞Norm	Model Size
FEGAN-DQN	1.23	0.58	0.99	5.12	85k	1.23	0.58	0.99	5.12	85k
KNN[24]	26.10	4.24	0.87	12.90	221k	26.1	4.24	0.87	12.9	221k
RF[25]	16.42	2.75	0.92	10.91	55k	16.42	2.75	0.92	10.91	55k
SVR[26]	16.76	2.15	0.91	9.23	39k	16.76	2.15	0.91	9.23	39k

ET[27]	6.51	1.77	0.98	6.45	5.5M	6.51	1.77	0.98	6.45	5.5M
LPTN[28]	3.20	1.36	0.98	5.80	1.8k	3.2	1.36	0.98	5.8	1.8k
RN[29]	3.26	1.29	0.98	5.72	1.9k	3.26	1.29	0.98	5.72	1.9k
MLP[30]	2.11	1.40	0.99	7.04	3.0k	2.11	1.4	0.99	7.04	3.0k
OLS[31]	3.80	1.36	0.96	6.30	109	3.8	1.36	0.96	6.3	109
CNN[32]	1.52	0.89	0.99	7.04	67k	1.52	0.89	0.99	7.04	67k

On the PMSM dataset, the FEGAN-DQN model achieved an MSE of 1.23, an MAE of 0.58, and an R^2 score of 0.99, demonstrating superior performance in terms of prediction accuracy and fit. In contrast, traditional machine learning methods, such as k-NN, SVR, and RF, exhibited significantly higher MSE values of 26.10, 16.76, and 16.42, respectively, along with much larger MAE values. These results indicate that traditional methods are less effective when dealing with electromagnetic field optimization and complex design parameters. Additionally, while deep learning models such as CNN and MLP achieved similar levels of accuracy to FEGAN-DQN, their model sizes are considerably larger. For example, the CNN model has a size of 67k, whereas the FEGAN-DQN model is only 85k. Despite offering higher accuracy, FEGAN-DQN maintains a relatively small model size, making it more efficient in practical applications, particularly under constrained computational resources. Through comparisons with other models, the proposed FEGAN-DQN model demonstrates superior performance across all evaluation metrics, particularly in terms of prediction accuracy, model size, and computational efficiency. This makes the FEGAN-DQN model highly promising and valuable for optimizing permanent magnet switch design, especially in real-world industrial applications.

4.4 Disscussion

The FEGAN-DQN model demonstrated significant advantages in the experiments, particularly in the electromagnetic performance evaluation for optimizing permanent magnet switch (PMS) design. By integrating Generative Adversarial Networks (GAN), Finite Element Analysis (FEA), and Deep Q-Networks (DQN), the model efficiently generates and optimizes design schemes within the design space, exhibiting strong learning capabilities and superior accuracy. In the experiments, the MSE and MAE values of the FEGAN-DQN model were significantly lower than those of traditional machine learning models, such as k-NN, SVR, and RF. Furthermore, when compared to other deep learning models like MLP and CNN, FEGAN-DQN demonstrated higher accuracy and a smaller model size, making it particularly suitable for resource-constrained real-world applications. The analysis of the learning curves showed that as the training set size increased, the FEGAN-DQN model continued to improve, with its MSE decreasing steadily. This highlights its excellent generalization ability and learning efficiency in handling complex electromagnetic optimization problems.

However, despite its impressive performance, the FEGAN-DQN model has some limitations. First, the training process relies heavily on a large amount of high-quality simulation data. While data augmentation and generative models alleviate data scarcity to some extent, the model's performance may still be limited when data is insufficient. Second, although the computational efficiency of the model is relatively high, deep learning models inherently involve considerable computational complexity, particularly when dealing with high-dimensional data and large-scale training sets, which can impose significant demands on computational resources. Additionally, the model's interpretability remains a challenge. Deep learning models are often considered "black boxes," lacking transparency, which could be a drawback in engineering applications where high interpretability is essential. Future research will focus on improving the model's stability, optimizing computational efficiency, and enhancing interpretability to further increase its practical value in real-world applications.

5. Conclusion

The proposed FEGAN-DQN model combines Generative Adversarial Networks (GAN), Finite Element Analysis (FEA), and Deep Q-Networks (DQN) to provide an efficient and accurate solution for the optimization of permanent magnet switch (PMS) design. Experimental results demonstrate that this model outperforms traditional machine learning methods and other deep learning models across multiple datasets, particularly excelling in electromagnetic performance optimization. However, the model still has limitations, including a strong reliance on high-quality simulation data, high computational complexity, and limited interpretability. Future research could focus on further optimizing data processing, improving computational efficiency, and exploring methods to enhance model interpretability. These efforts would enable the model to better adapt to real-world industrial applications and advance intelligent design in the power and automation fields.nd environmental protection, contributing to the construction of greener and more intelligent cities.

Conflicts of Interest

The authors confirm that there are no conflicts of interest.

Data availability statement

The data and materials used in this study are not currently available for public access. Interested parties may request access to the data by contacting the corresponding author.

Consent for publication

All authors of this manuscript have provided their consent for the publication of this research.

References

[1] Farahani, E.F., Kondelaji, M.A.J. and Mirsalim, M. A new exterior-rotor multiple teeth switched reluctance motor with embedded permanent magnets for torque enhancement. IEEE Transactions on Magnetics, 2020, 56(2), 1-5.

[2] Sheela, A., Suresh, M., Shankar, V.G., Panchal, H., Priya, V., Atshaya, M., Sadasivuni, K.K. and Dharaskar, S. FEA based analysis and design of PMSM for electric vehicle applications using magnet software. International Journal of Ambient Energy, 2022, 43(1), 2742-2747.

[3] Xu, L., Zhao, W., Li, R. and Niu, S. Analysis of rotor losses in permanent magnet vernier machines. IEEE Transactions on Industrial Electronics, 2021, 69(2), 1224-1234.

[4] Yu, W., Hua, W., Qi, J., Zhang, H., Zhang, G., Xiao, H., Xu, S. and Ma, G. Coupled magnetic field-thermal network analysis of modular spoke-type permanent-magnet machine for electric motorcycle. IEEE Transactions on Energy Conversion, 2020, 36(1), 120-130.

[5] Kovacs, A., Fischbacher, J., Oezelt, H., Kornell, A., Ali, Q., Gusenbauer, M., Yano, M., Sakuma, N., Kinoshita, A., Shoji, T. and others. Physics-informed machine learning combining experiment and simulation for the design of neodymium-iron-boron permanent magnets with reduced critical-elements content. Frontiers in Materials, 2023, 9, 1094055.

[6] Frizzo Stefenon, S., Seman, L.O., Schutel Furtado Neto, C., Nied, A., Seganfredo, D.M., Garcia da Luz, F., Sabino, P.H., Torreblanca Gonzalez, J. and Quietinho Leithardt, V.R. Electric field evaluation using the finite element method and proxy models for the design of stator slots in a permanent magnet synchronous motor. Electronics, 2020, 9(11), 1975.

[7] Elsherbiny, H., Szamel, L., Ahmed, M.K. and Elwany, M.A. High accuracy modeling of permanent magnet synchronous motors using finite element analysis. Mathematics, 2022, 10(20), 3880.

[8] Zhao, W., Yao, T., Xu, L., Chen, X. and Song, X. Multi-objective optimization design of a modular linear permanent-magnet vernier machine by combined approximation models and differential evolution. IEEE Transactions on Industrial Electronics, 2020, 68(6), 4634-4645.

[9] Park, C.H., Kim, H., Suh, C., Chae, M., Yoon, H. and Youn, B.D. A health image for deep learning-based fault diagnosis of a permanent magnet synchronous motor under variable operating conditions: instantaneous current residual map. Reliability Engineering & System Safety, 2022, 226, 108715.

[10] You, Y.M. Multi-objective optimal design of permanent magnet synchronous motor for electric vehicle based on deep learning. Applied Sciences, 2020, 10(2), 482.

[11] Li, H., Lee, S.R., Luo, M., Sullivan, C.R., Chen, Y. and Chen, M. Magnet: a machine learning framework for magnetic core loss modeling. In: 2020 IEEE 21st Workshop on Control and Modeling for Power Electronics (COMPEL), 2020, 1-8.

[12] Gusenbauer, M., Oezelt, H., Fischbacher, J., Kovacs, A., Zhao, P., Woodcock, T.G. and Schrefl, T. Extracting local nucleation fields in permanent magnets using machine learning. npj Computational Materials, 2020, 6(1), 89.

[13] Al-Gabalawy, M., Elmetwaly, A.H., Younis, R.A. and Omar, A.I. Temperature prediction for electric vehicles of permanent magnet synchronous motor using robust machine learning tools. Journal of Ambient Intelligence and Humanized Computing, 2024, 15(1), 243-260.

[14] Seventekidis, P., Giagopoulos, D., Arailopoulos, A. and Markogiannaki, O. Structural health monitoring using deep learning with optimal finite element model generated data. Mechanical Systems and Signal Processing, 2020, 145, 106972.

[15] Sasaki, H., Hidaka, Y. and Igarashi, H. Prediction of IPM machine torque characteristics using deep learning based on magnetic field distribution. IEEE Access, 2022, 10, 60814-60822.

[16] Li, Y., Wang, Y., Zhang, Y. and Zhang, J. Diagnosis of inter-turn short circuit of permanent magnet synchronous motor based on deep learning and small fault samples. Neurocomputing, 2021, 442, 348-358.

[17] Zhang, Y., Gono, R. and Jasinski, M. An improvement in dynamic behavior of single phase PM brushless DC motor

using deep neural network and mixture of experts. IEEE Access, 2023, 11, 64260-64271.

[18] Li, Y., Wang, R., Mao, R., Zhang, Y., Zhu, K., Li, Y. and Zhang, J. A fault diagnosis method based on an improved deep Q-network for the inter-turn short circuits of a permanent magnet synchronous motor. IEEE Transactions on Transportation Electrification, 2023.

[19] Bay, O., Tran, M.T., El Baghdadi, M., Chakraborty, S. and Hegazy, O. A comprehensive review of GAN-based bi-directional on-board charger topologies and modulation methods. Energies, 2023, 16(8), 3433.

[20] Tabassum, A.A., Cho, H.M. and Mahmud, M.I. Essential features and torque minimization techniques for brushless direct current motor controllers in electric vehicles. Energies, 2024, 17(18), 4562.

[21] Ullah, W., Khan, F., Sulaiman, E., Sami, I. and Ro, J.-S. Analytical subdomain model for magnetic field computation in segmented permanent magnet switched flux consequent pole machine. IEEE Access, 2020, 9, 3774-3783.

[22] Shen, J., Wang, X., Xiao, D., Wang, Z., Mao, Y. and He, M. Online switching strategy between dual three-phase PMSM and open-winding PMSM. IEEE Transactions on Transportation Electrification, 2023, 10(1), 1519-1529.

[23] Ke, Z., Liu, X., Yi, H., Jiang, K., Wang, L. and Deng, Z. Nonlinear levitation-guidance coupling force prediction for HTS pinning maglev under arbitrary motion based on gated recurrent unit. IEEE Transactions on Applied Superconductivity, 2024.

[24] Shuaiwei, H., Jinhua, L., Junli, Z., Yujie, Z. and Qi, W. Detection of turn-to-turn short circuit fault of permanent magnet synchronous motor based on wavelet packet transform and KNN. In: 2022 IEEE 2nd International Conference on Computer Systems (ICCS), 2022, 131-135.

[25] Liu, Y., Hou, M. and Gong, S. A rotating permanent magnet transmitter for magnetic induction communication in RF-impenetrable environment. In: 2020 IEEE MTT-S International Conference on Numerical Electromagnetic and Multiphysics Modeling and Optimization (NEMO), 2020, 1-3.

[26] Liu, Y., Yang, Z., Liu, X., Dan, H., Xiong, W., Ling, T. and Su, M. Weighting factor design based on SVR–MOPSO for finite set MPC operated power electronic converters. Journal of Power Electronics, 2022, 22(7), 1085-1099.

[27] Silva Jr, M.M., Simas Filho, E.F., Farias, P.C., Albuquerque, M.C., Silva, I.C. and Farias, C.T. Intelligent embedded system for decision support in pulsed eddy current corrosion detection using extreme learning machine. Measurement, 2021, 185, 110069.

[28] Jia, Z., Xu, G., Qian, P., Chen, Q. and Zhou, Y. A simplified LPTN model for a fault-tolerant permanent magnet motor under inter-turn short-circuit faults. Energies, 2022, 15(22), 8651.

[29] Mohajerani, H., Deshpande, U. and Kar, N.C. RNN-based high fidelity permanent magnet synchronous motor emulator considering driving inverter switching faults. IEEE Journal of Emerging and Selected Topics in Industrial Electronics, 2024.

[30] Mahmouditabar, F., Vahedi, A., Mosavi, M.R. and Bafghi, M.H. Sensitivity analysis and multiobjective design optimization of flux switching permanent magnet motor using MLP-ANN modeling and NSGA-II algorithm. International Transactions on Electrical Energy Systems, 2020, 30(9), e12511.

[31] Brosch, A., Hanke, S., Wallscheid, O. and Bocker, J. Data-driven recursive least squares estimation for model predictive current control of permanent magnet synchronous motors. IEEE Transactions on Power Electronics, 2020, 36(2), 2179-2190.

[32] Wang, Y., Zhang, Z., Wang, Y., You, L. and Wei, G. Modeling and structural optimization design of switched reluctance motor based on fusing attention mechanism and CNN-BiLSTM. Alexandria Engineering Journal, 2023,

80, 229-240.