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Review

The Review of Electromagnetic Field Modeling Methods for Permanent-Magnet Linear Motors

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Abstract: Permanent-magnet linear motors (PMLMs) are widely used in various fields of industrial production, and the optimization design of the PMLM is increasingly attracting attention in order to improve the comprehensive performance of the motor. The primary problem of PMLM optimization design is the establishment of a motor model, and this paper summarizes the modeling of the PMLM electromagnetic field. First, PMLM parametric modeling methods (model-driven methods) such as the equivalent circuit method, analytical method, and finite element method, are introduced, and then non-parametric modeling methods (data-driven methods) such as the surrogate model and machine learning are introduced. Non-parametric modeling methods have the characteristics of higher accuracy and faster computation, and are the mainstream approach to motor modeling at present. However, surrogate models and traditional machine learning models such as support vector machine (SVM) and extreme learning machine (ELM) approaches have shortcomings in dealing with the high-dimensional data of motors, and some machine learning methods such as random forest (RF) require a large number of samples to obtain better modeling accuracy. Considering the modeling problem in the case of the high-dimensional electromagnetic field of the motor under the condition of a limited number of samples, this paper introduces the generative adversarial network (GAN) model and the application of the GAN in the electromagnetic field modeling of PMLM, and compares it with the mainstream machine learning models. Finally, the development of motor modeling that combines model-driven and data-driven methods is proposed.

Keywords: permanent-magnet linear motor; parametric modeling; non-parametric modeling; surrogate model; machine learning; GAN

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1. Introduction

The permanent-magnet linear motor (PMLM) has the advantages of small size, high efficiency, and a simple structure. It avoids the mechanical conversion from rotary to linear motion, simplifies the structure, and improves the efficiency [1], Figure 1 shows a structure of the PMLM with slotted iron core [2]. PMLM also has an increasingly wide range of applications in industrial fields, such as high-speed linear servo, marine resource exploration, and oil drilling. Figure 2 shows a PMLM-driven oscillating hammer sampler for marine exploration.

In order to improve the performance of PMLMs, optimization design methods are widely used in motor design [3]. However, the prerequisite for the optimal design of PMLMs is to obtain their relatively accurate electromagnetic calculation models, which are commonly used in two categories: parametric modeling and non-parametric modeling [4,5].

The main methods for modeling electromagnetic field parameters include the equivalent magnetic network (EMN), analytical method, and finite element method (FEM) based on computer simulations. The EMN method is simple and computationally efficient, but the computational results are relatively coarse [6]. AM has high accuracy and computational efficiency, and some special linear motors such as slotless and coreless linear motors have almost linear magnetic circuits, because there is no core between the coils, and the AM model is relatively accurate [7]. However, for most PMLMs, the AM model accuracy is poor, due to its complex structure and the saturated non-linear characteristics of the magnetic circuit. FEM has the characteristics of high calculation accuracy and good adaptability, but its main problem is the large number of calculations and long consumption time, which is not suitable for direct use in the optimization program [3].

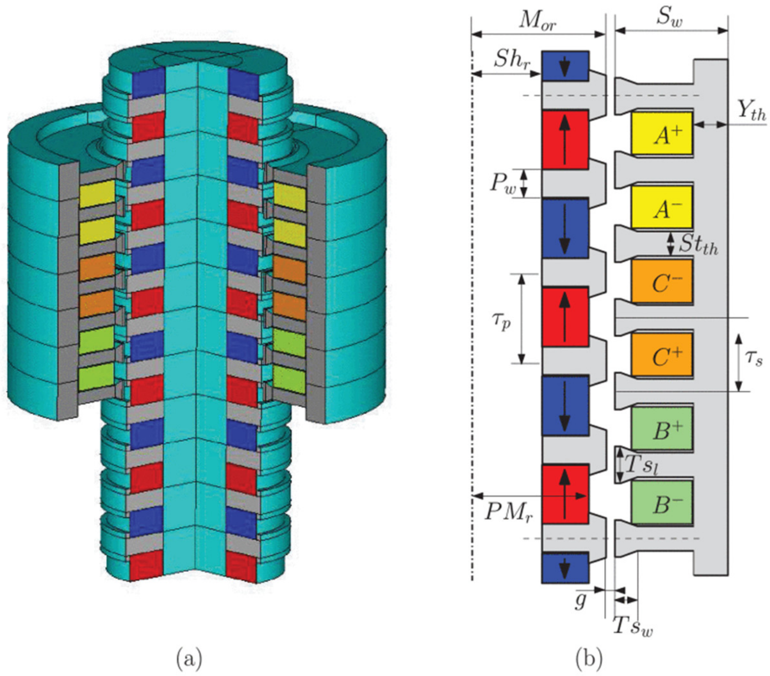

Figure 1. Structure of the PMLM with slotted iron core: (**a**) 3D view; (**b**) Plan view.

Figure 2. Structure of the oscillatory hammer driven by PMLM.

In order to address the limitations of the parametric models, some non-parametric modeling methods have gradually become a research topic of interest in PMLM optimization modeling. Non-parametric modeling usually refers to "black-box models", which approximate the real input–output mapping based on the input–output data of the object [8]. This type of modeling is data-driven, so it usually requires a certain amount of "real" data and uses these data to train a function approximator that can optimally or approximately optimally fit the input–output non-linear mapping relationship. Non-parametric modeling started with surrogate models such as response surface methodology (RSM), the Kriging model, and radical basis function (RBF) [3].

In recent years, non-parametric modeling methods represented by machine learning have also been applied to motor modeling, such as support vector machines (SVM) [9], random forest (RF) [10], artificial neural networks (ANN) [11], K near neighbor (KNN) [12], and extreme learning machine (ELM) approaches [13]. These methods have achieved good results in modeling the single electromagnetic field of PMLM with low dimensions. However, non-parametric modeling methods are only suitable for dealing with a few low-dimensional system models, or dealing with high-dimensional problems of system models, which requires a large amount of sample data. However, the sample data are often insufficient in motor modeling.

In this paper, the advantages and disadvantages of the existing parametric and non-parametric modeling methods are summarized based on the existing modeling methods for PMLMs. A GAN learning model is introduced after some of the latest machine learning modeling methods, and is compared with RF, SVM, and DNN methods.

2. Modeling Methods for Electromagnetic Field of Permanent-Magnet Linear Motors

When a motor operates, a magnetic field and electromagnetic phenomena exist in the area occupied by its internal space, copper (windings), and iron. This electromagnetic field is generated by the currents in the stator and rotor. The distribution and variation of the magnetic field in different media and the interaction with the current of the motor determine the operating state and performance of the motor. The performance analysis of the motor is based on the analysis and calculation of the electromagnetic field, and after obtaining the spatial magnetic field distribution, the magnetic field parameters such as flux density and flux can be derived, and then the force, torque, losses, reactance, and electric potential can be calculated [14,15]. Therefore, the performance analysis methods of electric motors rely heavily on the electromagnetic field analysis methods. Therefore, generally, when designing and analyzing a motor model, the first problem is to consider the electromagnetic field model in the motor.

2.1. Parametric Modeling Methods

2.1.1. Equivalent Magnetic Network (EMN)

An EMN is a modeling method that converts the electromechanical properties of a motor to a familiar circuit form using the principle of electromechanical analogy, and combining them into an equivalent circuit. It has the properties of relatively simple models and short computation time, and is a convenient tool for solving the practical problems of electric motors [16].

In [17], the EMN method was used to study the variation law of the PMLM end field by dividing the end of the motor into three regions, which can clearly and accurately calculate the end field of the whole motor and effectively improve the performance of the motor. A non-linear EMN model was proposed in [18]. The grid method was used to solve the magnetic fields in the air gap, magnet, and iron block. The EMN model was used to solve the air gap flux density distribution, from which the electric potential waveform, no-load cogging force waveform, and load force waveform were obtained.

The EMN method can better simulate the changes of the motor's electromagnetic field, and is a common parametric modeling analysis method for PMLM. The EMN method is simple and operationally efficient, and the optimization of linear motor parameters using the EMN method can greatly reduce the computational time of the search process. However, the method focuses on the analysis of the electrical characteristics of the motor and lacks sufficient physical interpretation of the circuit components [19]. To improve the computational accuracy, it is necessary to increase the number of grid nodes, which makes the workload increase significantly and loses its original advantage of small computational workload.

2.1.2. Analytical Method (AM)

The analytical method uses classical mathematical methods to establish the integral or partial differential equations describing the electromagnetic properties, and then solves them using the separation of variables method or the exchange mathematical method. This analytical method establishes the relationship between the thrust performance, motor structure parameters, and permanent magnet material performance, and is able to analyze some internal connections between various parameters of the object and its related calculations, which provides a theoretical basis for the design of motor structure and electromagnetic parameters.

The analytical method is often used in theoretical qualitative analysis due to the low accuracy of quantitative calculation [20]. A single-layer model for the coreless PMLM is presented in [7], and the accuracy of this single-layer AM is verified by comparing it with multilayer AM and FEM methods under different structural parameters. It is found that the AM is more accurate for some special linear motors such as slotless and coreless motors, where the magnetic circuit is almost linear because there is no core between the coils. Here, the AM has higher accuracy and computational efficiency, which can significantly reduce the computational cost.

The analytical method can directly reflect the relationship between the motor parameters and electromagnetic characteristics, which has guiding significance for motor design and optimization. However, with the continuous development of motor technology, new structures and principles of motors are emerging. For most PMLMs, the magnetic field distribution is complex due to the saturated non-linear characteristics of their magnetic circuits. It has been difficult to obtain accurate performance analysis results using the analytical method.

2.1.3. Finite Element Method (FEM)

The finite element method is currently the most widely used and effective method for analyzing the magnetic field of electric motors. It was proposed in the 1940s and applied to electromagnetic analysis in the 1960s. The finite element method, based on the variational principle, has been widely used in the quantitative analysis and optimal design of various electromagnetic fields due to its universal applicability. Its outstanding advantages are that it can handle complex motor non-linear parameter coupling, non-linear boundary, and other kinds of non-linear problems, and it is easy to implement standardized computer programs for calculation and has high solution accuracy. Figure 3 shows the FEM flow chart.

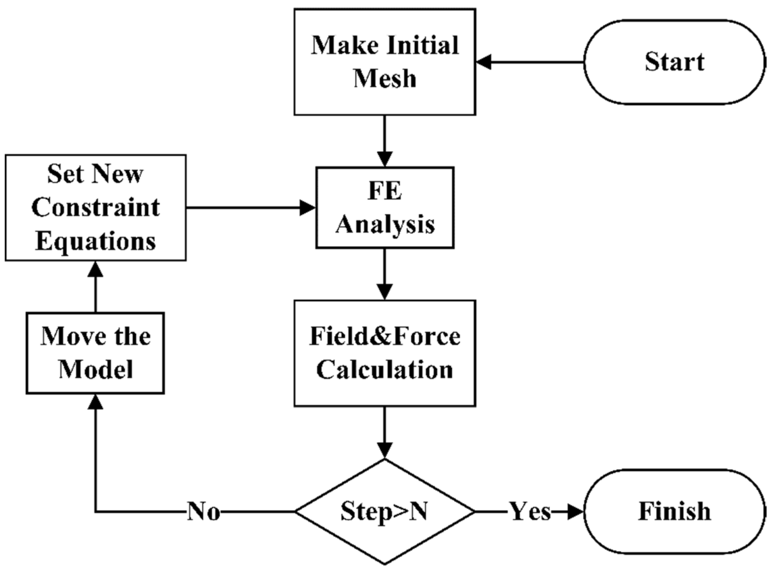

Figure 3. Finite element analysis flow chart.

In [20], the finite element method is used to establish the motor model. Compared with the analytical method, its calculation accuracy is greatly improved, but the calculation efficiency is low and cannot meet the real-time requirements in the process of optimization calculation. In [21], the method is used to obtain the air-gap magnetic field of a two-sided quadratic coreless PMLM, and this process establishes the magnetic field equations in different regions separately and then solves them simultaneously, which makes the solution process complicated and the analysis results complex. However, the biggest problem of the finite element method is that it cannot directly reflect the influence of the motor parameters on the electromagnetic performance, and the motor-related dimensional parameters must be adjusted using parametric modeling and repeated calculations with a large workload.

Compared with the AM, FEM has much higher computational accuracy, but lower computational efficiency and cannot meet the real-time requirements in the optimization computation process. FEM is suitable for modeling electromagnetic fields in various dimensions, with high computational accuracy and good adaptability, etc. Its main problem is that it is computationally intensive and time-consuming, which makes it difficult for application in certain high-speed optimization tasks [22] or for direct use in motor modeling optimization.

2.1.4. Summary

The above section introduced the application of parameter modeling methods in electromagnetic fields. It should be noted that the parametric modeling methods for motors are based on certain parametric equations. The input–output relations and the internal rules of the model are well defined. They require basic physical quantities and their interrelationships, and mathematical models are built using relevant mathematical derivation methods. However, in engineering applications, modeling methods may not always be based on parametric equations with explicit input–output relationships due to the uncertainty and non-linearity of the motor [22]. Therefore, modeling analysis using parametric models has certain limitations.

2.2. Non-Parametric Modeling Methods

Non-parametric modeling methods have the characteristics of higher model accuracy, fast computational speed, and powerful non-linear approximation capability. These methods are currently used in the mainstream for complex and non-linear electromagnetic field analysis of electric motors. Figure 4 shows the traditional non-parametric modeling methods classification.

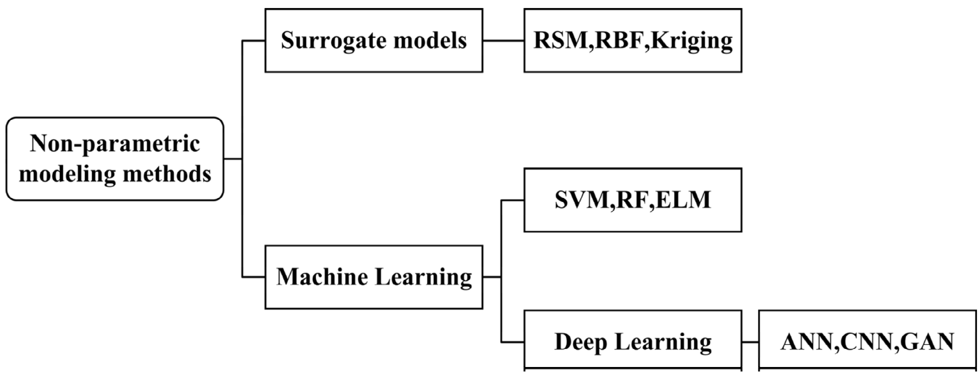

Figure 4. Non-parametric modeling methods classification diagram.

2.2.1. Surrogate Models

For many practical problems, a single FEM simulation may take minutes, hours, or even days to complete. Therefore, in order to obtain the optimal parameters of the motor, thousands or even millions of simulations may be required, thus solving directly for the original model would be impossible. One way to improve this situation is to use approximate surrogate models to simulate a high-precision model such as FEM. The computational results of the surrogate models are very close to the original models, but the solution is less computationally intensive. Surrogate models are mainly represented by the response surface methodology (RSM), Kriging, and radical basis function (RBF) [23]. In the past decades, these methods have been successfully applied to the optimal design of electromagnetic devices and systems, including PMLMs. These surrogate models ensure the computational accuracy of the models on the one hand, and the computational time of the parametric models is significantly reduced on the other hand [24–29].

1. Response Surface Methodology (RSM)

RSM is a linear model that estimates each parameter of the model using the least squares method. It uses multiple linear regression equations to fit the functional relationship between the parameters and response. Since RSM is a linear model, it is simple and basic, and it takes little computational effort. In [30–32], RSM was used to model and optimize the permanent magnet (PM) type of transverse flux linear motors (TFLMs); it reduced the machine weight under thrust and braking force constraints, and the results showed that RSM can model the minimum weight analysis under thrust and braking force constraints well in the case of a small number of parameters and low dimensions. Moreover, a considerable amount of computational time can be saved compared to FEM. However, RSM cannot be used in modeling with high parameter dimensionality, and when the range of parameter values is large and the relationship between the parameters and response is complex, the fitted model will be meaningless or the difference between the optimization results and simulation results will be large [33].

2. Radical Basis Function (RBF)

RBF neural networks, which are a forward neural network type, have a strong non-linear function approximation capability and self-learning ability to approximate any continuous function with arbitrary accuracy. RBF is more complex than RSM because the model basis function of RBF has additional shape parameters [34], so it can handle higher dimensional data [35]. RBF has good noise immunity and is not easily overfitted; based on these characteristics, RBF is generally used in traditional motor PID control. In [36], RBF is used to adaptively adjust its non-linear input so that the input signal can become linearly differentiable in a high-dimensional space, thus improving the control accuracy of the system and ensuring the stability of the motor's operation. However, when RBF model has a large number of parameters, the space and time required for training can be large.

3. Kriging

Kriging is a regression algorithm for spatial modeling and the prediction (interpolation) of stochastic processes/fields based on the covariance function. It estimates not only the coefficient matrix under the deterministic term, but also the parameters in the variance and correlation functions under the stochastic process term [37]. In [38], the motor is modeled by constructing a difference function using Kriging that approximates the objective function. It reduces the fluctuations, vibrations, and noise generated by the PMLM thrust. A Kriging method based on Latin hypercube sampling (LHS) is used in [39] to model the PMLM parameters that affect the torque of the magnetic group in order to obtain the optimal rotor shape and, thus, a larger speed regulation range.

Kriging is also capable of forming hybrid algorithms with other models, such as a Kriging model based on expected improvement (EI) and an adaptive-sampling Kriging algorithm (ASKA) proposed in [40,41], respectively, and the average thrust can be increased while reducing motor thrust fluctuation and torque pulsation. The hybrid algorithms aim to reduce the number of samples needed for the model by optimizing the model and greatly reducing the number of function calls as a way to significantly reduce the computational costs. Although Kriging is better optimized for local non-linear modeling compared to the RSM and RBF models [42], as the dimensionality gradually increases, Kriging requires more samples and will be more sensitive to noisy data [43]. At the same time, the Kriging response surface will pass through all sample points, and if the sample points are too many and too complex, it will lead to overfitting and lead to failure of the model construction.

4. Summary

The best choice of surrogate model depends on the type of motor optimization. RSM is suitable for simple and low-dimensional motor thrust optimization, RBF is suitable for PID control of motors, and Kriging is usually used for modeling and optimizing motor parameters by choosing different regression functions according to the actual need. Table 1 compares the widely used surrogate models.

Table 1. Comparison of widely used surrogate models.

Model	RSM	RBF	Kriging
Model basis functions	Linear and quadratic polynomials	Gauss, multiquadric, and inverse multiquadric	Constant, linear, and quadratic polynomials
Estimation method	Least square method	None	Best linear unbiased and maximum likelihood estimation
Complexity	Relatively low	Middle	Relatively high
Advantage	Simple and basic Small calculation volume	High accuracy rate Not easy to overfit Can process high dimensional data	Superiority in local non-linear modeling Response surface can pass through all sample points
Deficiency	Small range of values Easy overfitting	Excessive training time and space when there are more decision trees	Sensitive to noisy data Less efficient for low-order functions or high-dimensional problems

Common surrogate models are usually dedicated to a problem and describe the system with few parameters, thus limiting the ability of any possible changes in motors' design. Moreover, most surrogate models can only handle low-dimensional parameters and have no autonomous learning capability. However, with the increasing dimension of motor electromagnetic field modeling, the analysis becomes more complex, and the applicability of the surrogate models is gradually reduced.

2.2.2. Machine Learning Models

1. Support Vector Machine (SVM)

SVM is a machine-learning method based on statistical theory proposed by Vapnik et al. in the late 1990s [44]. It is built on the principle of structural risk minimization (SRM), specifically for modeling motors with low dimensions and few samples, and it has the advantages of adaptive learning ability and non-linear approximation.

The original support vector machine (Vanilla SVM) was designed to deal with binary classification problems. Some improved versions have been proposed in order to extend it to multi-class classification [45]. A new decoupled control method for permanent-magnet synchronous motors was proposed in [46], which uses a new support vector machine generalized inverse (SVMGI). The coupling reactions within the PMLM system are eliminated, and the robustness and dynamics of the load is improved. To address the limitations of SVM in high-dimensionality modeling, a multiple support vector machine (multi-SVM) was proposed in [47], where a non-parametric fast computational model is developed by mapping the relationship between multivariate structural parameters and multivariate operational performance. This improves the performance of PMLMs in terms of motor thrust, thrust ripple, and induced electric potential.

In [9], SVM was used to develop loss prediction models for PMLM copper loss, iron loss, and eddy current loss at arbitrary frequencies. Two common metrics, decision coefficient (R^2) and explainable variance (E_{var}), are used to represent the computational accuracy. As shown in Table 2, the SVM model exhibits a lower generalization error rate and faster convergence compared to Fourier-transform (FT) and artificial neural network (ANN) in the analysis of low dimensions and few samples.

Table 2. The accuracy comparison of models based on different methods.

Method	Modulus (Ω)		Phase (Rad)		Cost Time(s)	
	R^2	E_{var}	R^2	E_{var}	Modulus	Phase
FT	0.951	0.689	0.883	0.553	0.055	0.288
ANN	0.967	0.702	0.896	0.613	0.312	0.342
SVM	0.988	0.842	0.941	0.784	0.012	0.013

Compared with other intelligent motor-modeling methods, SVM has a unique advantage, especially in small sample data processing, due to its excellent non-linear mapping capability and unique associative memory capacity based on statistical and structural risk minimization [9]. However, the parameter optimization of support vector machines has been one of the most important issues, and there is no general kernel function to optimize the SVM parameters [48]. Therefore, SVM is only applicable to some simple low-dimensional non-linear problems. Although it is not as general as neural network (NN), SVM is still one of the more promising machine learning algorithms for motor modeling.

2. Random Forest (RF)

RF is an algorithm that integrates multiple trees through the idea of ensemble learning. Since 2001, RF has received much attention from various research fields. As a new prominent algorithm, it is mainly used in classification and prediction. RF is able to handle high-dimensional data without feature selection, and it also has a strong anti-interference ability. When there is a large amount of missing data, modeling and analysis can also be processed by RF. Based on these characteristics, RF is widely used in motor control and fault diagnosis [49–53].

In [54], a two-level inverter scheme based on an RF regression algorithm was proposed to improve the performance of a three-phase induction motor drive. It provides the advantages of fast implementation and prediction improvement for space vector pulse-width modulation.

However, RF cannot give continuous output and does not perform as well as it does in classification when solving regression problems. When performing regression prediction modeling, although RF can solve some missing data problems, it cannot make predictions beyond the range of the training dataset, which may lead to overfitting in some cases where there are specific noisy data in the model. In contrast to SVM, RF cannot produce good classification for small sample data or low-dimensional data.

3. Extreme Learning Machine (ELM)

ELM can map complex non-linear relationships between inputs and outputs through data-driven machine learning. It is suitable for both supervised and unsupervised learning problems. ELM can randomly select input weights and biases and then determine output weights by simple matrix calculations instead of using traditional gradient-based learning methods [55–58]. Traditional ELM has a single hidden-layer feedforward neural network, which has advantages in terms of learning rate and generalization ability when compared with other learning systems, such as single-layer perceptron and SVM [59].

The literature [60] introduced ELM to map the non-linear relationship between the demagnetization characteristics of permanent magnet materials to establish a demagnetization model, and verified the effectiveness and advancement of the method using comparison experiments with the linear modeling method and polynomial modeling method. The literature [13] solves the computational modeling problem by employing ELM to map the non-linear complex relationship between the input structural factors and the output motor performance; the optimal performance of PMLM with average thrust, thrust pulsation, and total harmonic distortion (THD) was obtained at different speeds. Figure 5 shows the accuracy comparison results, which demonstrate the higher accuracy of ELM for PMLM modeling.

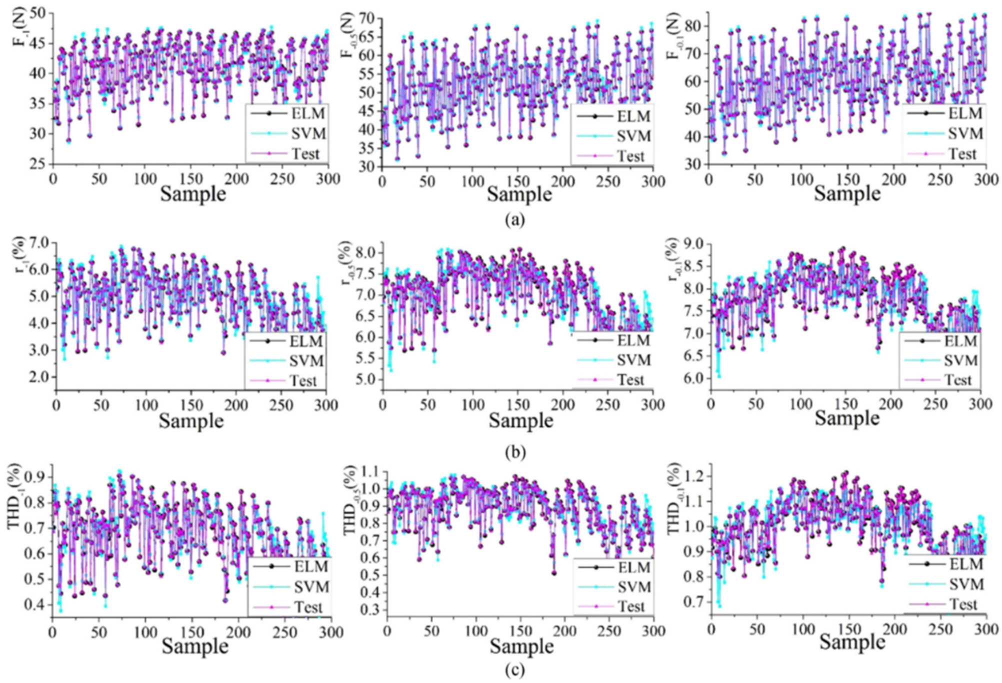

Figure 5. Accuracy test results of ELM: (**a**) Accuracy test of average thrust at different speeds; (**b**) Accuracy test of thrust pulsation at different speeds; (**c**) Accuracy test of THD at different speeds.

However, since ELM only has a single hidden-layer feedforward neural network, its structure determines that it is not as capable of representing extremely complex non-linear models as deep learning models.

4. Deep Learning Models

Deep learning is a new research direction in the field of machine learning. Deep learning differs from traditional machine learning in that it emphasizes the depth of the model structure. The concept of deep learning originated from the study of artificial neural networks (ANN). An ANN is able to model any multidimensional non-linear relationship with any desired accuracy, using simple and fast model computation and learning and generalization from the available data [61]. In motor modeling, an ANN is usually used to extract and filter the input part of the information layer-by-layer, and the back propagation algorithm guides the correlation and its adjustment to correct the internal parameters so that the computer finds the relationship that is implicit in the internal data, thus achieving the purpose of extracting the data features.

In [62], an ANN-based L_P metric technique was proposed to model and optimize the three objective functions: efficiency, speed, and material cost of a permanent-magnet brushless DC. Compared with the conventional analytical model, ANN-based model optimization can achieve higher motor speed and less magnet weight, resulting in higher output power and lower cost. In [63], parameters such as PMLM torque and the linked fluxes were optimized, and various modeling strategies were compared: linear regression (LR), SVM, RF, and ANN. The motor models were optimized using the above technique and then their accuracy was compared based on FEM simulations. The highest accuracy was achieved for the model using ANN.

Neural networks have various architectures. The convolutional neural network (CNN) is the most common framework, and the classification accuracy of CNNs outperforms many other traditional methods. In motor modeling and optimization, CNNs are able to replace FEM to accelerate multi-objective topology optimization and also to perform a rapid evaluation of the motor performance. In [64], CNNs were trained in a supervised manner using the data generated by a finite element analysis solver to build a fast and general data-driven model for PMLM electromagnetic device analysis, design, and optimization. It provided guidance for selecting the most appropriate network designs for future work in this area. A deep learning-based algorithm for motor topology optimization was proposed in [65,66]. In [65], the average torque and torque pulsation values of PMLM are accurately inferred through the transfer learning of small data. The computational cost of topology optimization for both motor models can be reduced by 15% and 13%, respectively, compared to the conventional method without CNN. CNN was used in [66] to accurately classify the average torque and torque pulsation of PMLM. However, that paper did not use CNN to infer other motor characteristics such as iron, copper consumption, and radial magnetism.

5. Summary

The non-parametric modeling method is a data-driven approach. It combines the characteristics of FEM model accuracy and fast calculation speed, and has powerful non-linear approximation capability, which is the mainstream direction of motor electromagnetic field analysis at present.

Compared with surrogate models, traditional machine learning models have stronger generalization ability, can handle different kinds of modeling optimization problems in higher dimensions, and the models are more intelligent and can perform some degree of self-learning as needed. Machine learning has achieved good results in modeling a single electromagnetic field with low dimensions for PMLM. However, traditional machine learning modeling processes such as SVM are complicated, the performance of modeling is highly correlated with the kernel function, the generality of the kernel function is not strong, and the performance on complex non-linear fitting problems is poor. Although SVM and ELM are suitable for small sample data, they do not have sufficient representation capability for non-linear systems with high dimensionality, and when dealing with high-dimensional problems, RF requires a large amount of sample data, which is prone to non-convergence when the sample data is small, which is the biggest problem limiting its application. Traditional machine learning methods for modeling problems of high-dimensional systems require a large number of samples; however, the samples need to be obtained from parametric modeling methods, and the current popular methods for parametric modeling such as FEM are too time-consuming.

Deep learning is applicable to various high-dimensional non-linear data processing, and it has strong learning ability and high fault tolerance, but it also has the defects of poor generalization ability, over-learning, and low learning efficiency, and it is easy to fall into local minima. In addition, the choice of the structure of the neural network and the selection of some training parameters are highly dependent on personal experience. Most deep learning models require a large number of samples to learn adequately, and the source of the samples is generally based on FEM, which increases the workload and reduces the operability of this data-driven modeling approach. Table 3 compares the traditional machine learning model and the deep learning model.

Table 3. Comparison for traditional machine learning and deep learning models.

Model	Traditional Machine Learning	Deep Learning
Training sample requirement	Low or middle	Relatively high
Self-learning ability	Middle	Relatively high
Generalization capability	Relatively high	Relatively low
Complexity	Middle	Relatively high
Deficiency	Unable to handle high-dimensional non-linear problems	Easy to overfit and fall into local minima Low learning efficiency

In order to address the limitations of the abovementioned PMLM non-parametric modeling methods, this paper introduces the generative adversarial network (GAN) model and introduces the application of GAN in the modeling of PMLMs, and compares it with the mainstream machine learning models.

3. Non-Parametric Modeling Method Based on Generative Adversarial Network

3.1. Generative Adversarial Network (GAN)

The GAN is a deep learning model and is one of the most promising methods of unsupervised learning on complex distribution developed in recent years [67]. The model generates better outputs by learning from the mutual game of two deep learning neural networks (generator G and discriminator D) in the framework. The generator G and the discriminator D each have a loss function, which can be trained to make the network parameters of the generator and the discriminator locally optimal, so that the difference between the two networks can be obtained as a minimum. Specifically, G is used to generate samples from the same distribution of training data, and D is used to check whether the samples generated in G are true or not. D classifies the output into two categories: true or false. It tries to label the samples true from the true training data and false from the generated data of G.

- Input enhancement of discriminator D: for the phenomenon that the small sample learning of GAN may cause degradation of the generator G. Since the original discriminator D has a strong discriminative ability, the improved design is proposed to let the discriminator D guide the generator G away from the degenerate direction. We introduce the contrastive learning of self-supervised learning theory to D. We construct the inputs of D as follows:

$$y = \begin{cases} y_1^p = cat(x, x) \\ y_1^N = cat(G(z), x) \\ y_2^N = cat(G(z), G(z)) \\ y_3^N = cat(x, G(z)) \end{cases} \quad (1)$$

  where x is a set of real data in a mini batch, z is a set of hidden variables in a mini batch, which come from some prior probability distributions and can be regarded as noise, $G(z)$ is the output of the generator G, $cat()$ is the concatenation function, y_1^p is a positive sample that can be regarded as y in Figure 6, and y_1^N, y_2^N, y_3^N are three groups of negative samples that can be regarded as y' in Figure 6. Through such a construction of positive and negative samples, the number of training samples for D is twice as large as the original data, and the difference between the positive and negative samples becomes larger. We label the positive samples y as 1 and the negative samples as 0 and use them to train the discriminator D. The discriminator D can be viewed as a binary classifier, and the loss function of the discriminator D can use the regular loss function of GAN. The construction of the above input enhancement and loss function enables the discriminator D to guide the generator G to evolve in the correct direction.
- Input enhancement of generator G: more suitable generation samples are obtained by the enhancement of the generator G input. The most important feature of GAN is that the input z of the generator G can be information from some prior probability distributions (noise) and can also contain a large number of pseudo-samples provided by the computational model of the motor physics field resolution. This process will generate more training samples to train G, and the input of G is constrained so that $G(z)$ is not a random output. Since the task of G is regression, the loss function of G can be designed as the Mean Square Error between $G(z)$ and the true samples.

The above design provides part of the idea for the problem solutions that GAN tends to fall into pattern collapse and produce suboptimal probability distributions when the sample data are insufficient.

Figure 7 shows the basic structure of GAN in an electromagnetic field.

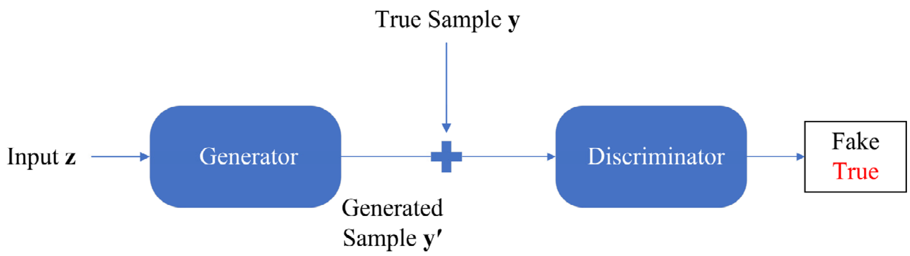

Figure 6. Basic structure of GAN.

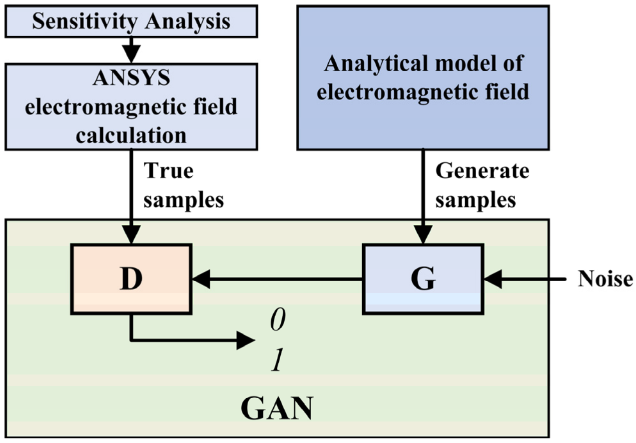

Figure 7. Basic structure of GAN in electromagnetic field.

3.2. Non-Parametric Modeling Based on GAN

We use GAN to carry out a regression task of the non-parametric modeling of TPMLM. TPMLM has four main design parameters: permanent magnet length c, slot width b, slot height d, and air gap length e. We use a vector v to represent them, $v = [b, c, d, e]$. The goal of our regression mission is to obtain a G, which fits the following equation.

$$\boldsymbol{G}(z) = \boldsymbol{T} = \sigma(v) \quad (2)$$

where σ represents a complex non-linear function, $\boldsymbol{T} = [T_{mean}, T_{\mathrm{var}}, H]$. T_{mean} denotes the mean thrust, T_{var} denotes the variance of the thrust, and H represents the economic indicator (this part is mainly the usage amount of permanent magnets). T and v are collected using finite element analysis modeling.

The optimization method for both the generator and the discriminator is the Adam algorithm [68] and uses the same parameters with a learning rate of 0.001 and a coefficient β = (0.5, 0.999) used to calculate the running average of the gradient and its square. The generator and discriminator were trained using a simultaneous gradient descent strategy with a training period of 12,000 rounds.

3.3. Simulations and Results

To validate the proposed GAN, we chose SVM, RF, and deep neural networks (DNN) as baselines. To ensure fairness, the depth of the DNN and RF was the same as that of GAN. In addition, DNN had the same structure and parameters as the G of GAN. The training strategy and optimizer also remained the same as GAN. The size of the dataset collected from the FEM was 2530. We divided it into 700 training data and 1830 test data.

Figures 8–10 show the comparison of the mean thrust, thrust variance and economic index prediction of the PMLM models built by proposed GAN and baseline methods. It can be clearly seen that the two deep learning methods (GAN and DNN) achieved much better performance than the other two traditional machine learning methods. Furthermore, the GAN predictions are closer to the true values than DNNs. In order to compare the performance of each method more rigorously, Table 4 shows the RMSE of the triple objective model built by each method on the test set compared to the training set. GAN also outperforms the other models.

Table 4. RMSE for all methods.

	GAN	DNN	SVM	RF
Test	0.03834	0.03843	0.1011	0.05547
Train	0.03832	0.03942	0.09580	0.05730

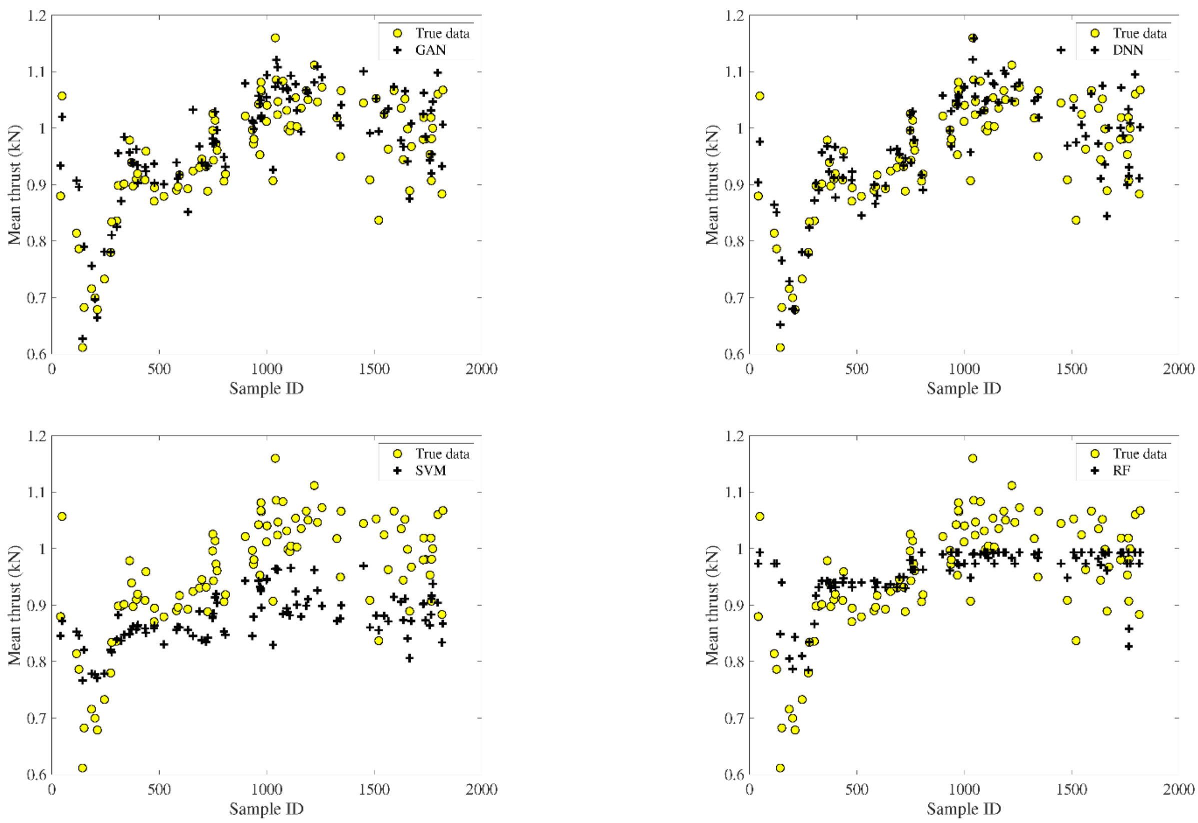

Figure 8. Comparison of the mean thrust prediction of the PMLM models built by proposed GAN and baseline methods.

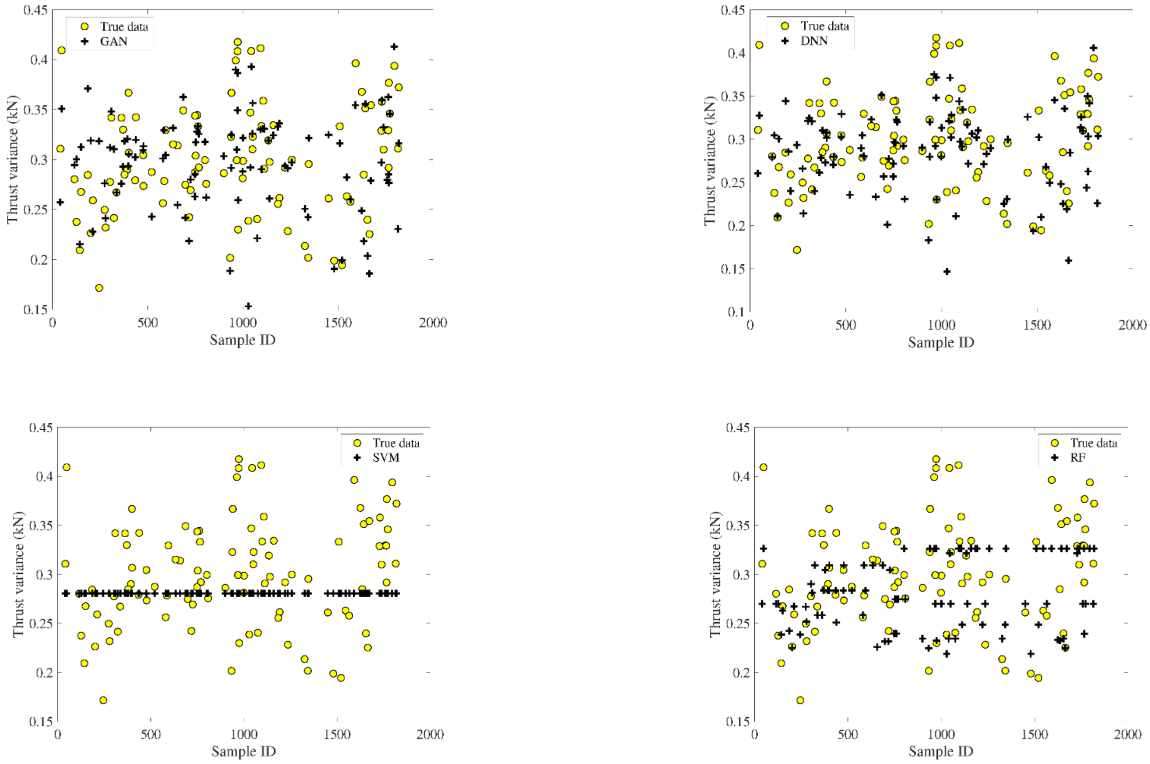

Figure 9. Comparison of the thrust variance prediction of the PMLM models built by proposed GAN and baseline methods.

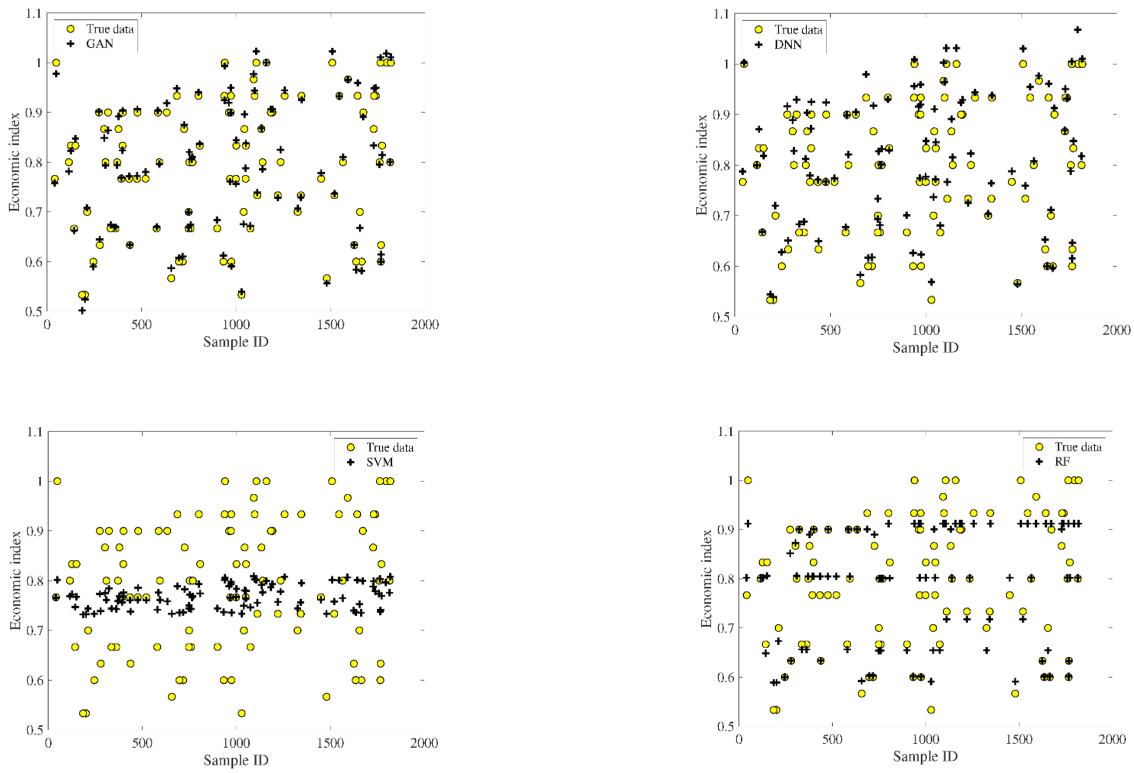

Figure 10. Comparison of the economic index prediction of the PMLM models built by proposed GAN and baseline methods.

4. Conclusions and Future Directions

This paper introduces some approaches to PMLM modeling, including model-driven parametric modeling methods such as the equivalent magnetic network, analytical method, and finite element method, and data-driven non-parametric modeling methods such as the surrogate model, machine learning, and deep learning, and summarizes these methods accordingly. A non-parametric modeling method based on generative adversarial networks and its applications are emphatically introduced, and compared with the traditional non-parametric modeling methods. The results have better fitting accuracy, which verifies the effectiveness and advancement of this method, and also provides a new research direction for future PMLM modeling.

The parametric modeling method has the problem of low model accuracy or time-consuming calculations. The non-parametric modeling method has better model accuracy and calculation speed, which is the current mainstream approach to the analysis of complex, non-linear magnetic fields of electric motors. Whether using parametric modeling or non-parametric modeling methods, the current source of the sample data generally uses finite element methods, which significantly increase the workload and also make it difficult for the computational efficiency to meet the motor optimization needs. Therefore, the different modeling methods of PMLM have the common problem of insufficient real sample size in practical applications. How can a small amount of sample data be used to achieve an efficient and high-accuracy calculation model of an electromagnetic field? Small sample data reduces the workload of obtaining sample data and simplifies the computational effort of non-parametric modeling. The existing non-parametric modeling methods, whether classical surrogate models (RSM, Kriging, RBF) or machine learning models, treat the physical model of the motor as a black box and rely on a large amount of data to establish the relationship between the input and output, which is detached from the physical nature of the electromagnetic field. Future research directions can be considered as follows: learning from a limited number of examples with supervised information to achieve few-shot learning (FSL), such as meta-learning, embedding learning, and migration learning [69], and taking this theory into motor modeling optimization. At the same time, a deep integration of model-driven combined with data-driven can be considered.

Motor modeling needs to consider the multi-field coupling problem, and current model calculations generally use indirect coupling, i.e., alternating iterative methods for solving, which brings additional computational overheads. The main way to improve computational efficiency is to improve the computational efficiency of individual physical fields. In the future, we can consider using FSL to prepare the physical field models, calculate two independent models separately, iterate the computational output results with each other, and dynamically set the iteration thresholds by combining the ranges of coil temperature rise and permanent magnet temperature rise, so as to reduce the number of iterations of multi-field indirect coupling as much as possible.

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