Research Article

Gearshift Sensorless Control for Direct-Drive-Type AMT Based on Improved GA-BP Neural Network Algorithm

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The automated mechanical transmission (AMT) based on the electromagnetic linear driving device (EMLDD) has good potential for shift performance. However, the direct-drive shifting mechanism based on the displacement sensor is difficult to meet the compactness of the structure and control robustness in complex environment. Through analyzing the working principle of the electromagnetic linear driving device and features of sensorless control strategy, a new displacement prediction method based on the improved GA-BP neural network is proposed to replace the displacement sensor. With current, voltage, and input shaft speed of the electromagnetic linear driving device as input, displacement prediction is obtained by the GA-BP neural network with improved selection factor. Finally, the experiment validated the effectiveness of displacement prediction based on the improved GA-BP neural network of shift control. The results showed that prediction accuracy of the improved GA-BP neural network was greater than 96% under all shift working conditions. The average RMSE was reduced by 21.8%, absolute error of displacement prediction was controlled within ±0.5 mm, and average shift time was less than 0.18 s. In this paper, the BP neural network is applied to complex linear displacement prediction, which has important application and popularization value.

1. Introduction

With the continuous development of linear motion mechanism, more and more direct-drive mechanism is applied to various complex linear motions. A novel AMT gearshift system based on direct-drive technology has developed a completely improved electromagnetic linear driving device, which works as a gearshift actuator [1]. As an energy conversion device, electromagnetic linear drive device converts external electric energy into mechanical energy through magnetic field to drive the mechanism to achieve linear motion. The electromagnetic linear drive device adopts the moving coil structure, and the permanent magnets are arranged in accordance with the Halbach array to reduce the thrust fluctuation and alleviate the influence of the end effect [2, 3]. Direct-drive-type AMT gearshift system with electromagnetic linear drive device has tremendous potential to minimize the shifting time of AMT. Direct-drive technology eliminates the shift control structure and reduces the number of moving parts in the transmission, improved robustness and dynamic response of the gearshift system, reduced energy consumption, and has increased transmission efficiency and improved shift quality.

The development in modern control technology guarantees the safety of equipment and personnel during operation [4, 5] and also guarantees the accuracy of linear motion control. Perception of position measurement is an indispensable course of the electromagnetic linear driving device motion control process [6–8]. Displacement feedback on the control system is the key factor to achieve the precise control of movement [9, 10]. The most common approach is to install the displacement sensor on each electromagnetic linear driving device, but this introduced a number of displacement sensors, increases the system cost, and takes up more installation space. The existence of displacement sensor limits the cost, motion characteristics, operational reliability, and application range of the system [11]. In addition, it is susceptible to electromagnetic interference when packed in the same shell as the actuators. Once the displacement sensor fails, the actuation system cannot work...
normally [12]. In order to overcome these shortcomings, the sensorless control scheme was adopted in this paper. In recent years, sensorless control technology has gradually become a hot topic of linear driving device research. The mature high-speed digital signal processor technology (DSP) has become the hardware guarantee of sensorless technology development. DSP can meet the demand of high-speed real-time processing of large amount of data and can be applied to the real-time calculation of sensorless displacement prediction technology.

The elimination of the displacement sensor simplifies the structure of the gearshift system and reduces the manufacturing cost. Sensorless control provides many advantages over a single actuator/sensor system, such as low cost, simplicity, and robustness [13, 14]. In this context, a great number of papers had been presented for the piezoelectric actuator [15], bistable permanent magnet actuator [16, 17], induction motor [18, 19], and permanent magnet synchronous machines [20]. Sensorless technology is applied to the prediction of rotation angle, rotation speed, position, and other variables of various rotary and linear motion systems, showing good results in different fields. The sensorless control technology started in the 1980s and is now widely used in various applications. The most common sensorless control technology is used for rotary motors and linear motors, which are mainly used for estimating motion parameters such as rotor position and rotor speed. At present, there are two kinds of prediction methods for motor parameters. One is based on the mathematical model of the motor, including direct calculation method, adaptive method, and sliding mode observer. In particular, Luenberger observer [21], extended Kalman filter [22], or sliding mode observer [23] is widely used to estimate positions. The other is based on the motor salient pole effect, including high-frequency signal injection method.

These methods require relatively accurate mechanical models, which are often difficult to obtain. In [24], a method that measures the current of brushed dc motors and analyses the position of its spectral components is proposed. From these spectral components, the method estimates the motor speed. This method is not based on either the dynamic model or the ripple component and achieves a low error in the speed estimation. In [25], the mathematic model of the self-sensor was established by analyzing the moving magnet linear motor of linear compressor; the measurement method of the piston stroke was achieved, and the steady-state estimation error of the mover displacement is less than 5%. Therefore, the input physical signal and EMF contain information such as rotor position and speed; by analyzing and demodulating the required parameter information, the sensorless prediction is realized [26, 27]. In [28], the design and operation of a special electromagnetic actuator as a variable engine valve actuator are presented and build reduced-order observers for estimating the velocity of systems through the measurement of input current and voltage. The robustness of the velocity tracking is explored using a minimum variance approach.

An observer can also be used to compensate the estimation error to obtain a better closed-loop control effect. Using the variables in the original system as the input of the new system, the reconstructed state variables of the new system is gradually equivalent to the state variables of the original system under certain control conditions. Kalu et al. [29] aim at the problem that the force cannot be directly measured in the remote-control process of the dismantling robot of nuclear facilities; the control strategy is developed by using sliding mode control with sliding perturbation observer (SMCSPO). It can estimate the reaction force at the end effector and second link without using sensors. In [30], an improved sliding mode observer (SMO) is proposed to estimate the rotor position and the speed of the proposed machine based on Vernier permanent magnet machines. The maximum power point tracking (MPPT) control strategy is applied to maximize the wind power extraction.

In addition, the research of using the intelligent algorithm to predict parameters is developing gradually; particle swarm optimization (PSO) [31], genetic algorithm (GA) [32], neural network (NN), and other intelligent algorithms have been widely used in the field of sensor-free research. Gutiérrez-Villalobos et al. [33] proposed a new kind of estimator for control schemes for neural network and control theory based on three-phase asynchronous motor, which is used to improve the defense ability of magnetic directional control against external changes. This estimator adjusts its set of weights in order to update these two values (speed and rotor resistance), which improves FOC algorithm behavior. Yu et al. [34] proposed a dynamic full parameter auto-adapted BP neural network using a combination of simulated annealing algorithm (SA), genetic algorithm (GA), and BP neural network and applied it to the prediction of oil and gas reserves. By comparing the GA-SA network, GA-BP network, and GA-SA-BP network for the prediction of oil and gas reserves, we can get that the GA-SA-BP network has better precision and generation. In addition, GA and BP algorithms are also used in stock forecasting and weather forecasting scenarios.

This paper aims at the moving coil electromagnetic linear driving device, proposed a sensorless control method based on the improved GA-BP algorithm, by improving the selection factor of genetic algorithm, and conducted sensorless control tested based on measurement and control system. The rest of the papers is organized as follows. The direct-drive shifting system overview and electromagnetic linear drive device are introduced in Section 2. In Section 3, the design process of position sensorless based on the GA-BP neural network is introduced in detail. Section 4 mainly analyzes the network prediction results and experimental results. Finally, the paper is concluded in Section 5.

2. Direct-Drive-Type Automated Manual Transmission System

2.1. Direct-Drive-Type AMT System Overview. A new direct-drive-type AMT gearshift system based on two-speed transmission was mainly composed of the electromagnetic linear driving device, transmission, shift fork, and displacement sensor. The electromagnetic linear driving device
directly drives the shift fork to complete the shift movement. Figure 1 shows the structure of the direct-drive-type AMT.

The system has the following advantages: simplifies the system structure and enhances the robustness. The crank, connecting rod, and other motion conversion devices are eliminated, which improve mechanical efficiency and reduce mechanical hysteresis, compliance, and backlash. Adoption of the electromagnetic linear driving device which has high drive ability and fast dynamic response is beneficial to the reduction of gearshift time and improvement in shift quality.

In order to simulate the actual working condition of the direct-drive-type AMT gearshift system of electric vehicle, the measurement and control system of the direct-drive-type AMT gearshift system are established. Figure 2 is the structure diagram of the measurement and control system.

In the process of gearshift, computer sent control instructions to DSP based on the control strategy, and the power driving circuit generates PWM control signal according to DSP, amplifying the signal to drive the electromagnetic linear driving device. Figure 3 shows the test bench of measurement and control system of the electromagnetic linear driving device.

The focus of this paper was the gearshift process after the motor stops output torque. According to different research purposes, the gearshift process can be divided into several phases. Prior to the synchronous process, the synchronizer ring moves forward to eliminate the gap between the synchronizer ring and the friction cone. When the friction torque appears, the synchronous process begins and the rotation speed difference decreases. Synchronizer ring moves forward again and finally completed the engagement with the target gear when the speed difference disappears. For the direct-drive-type AMT gearshift system, the shift synchronous process was divided into two main phases, the nonsynchronization phase and the synchronization phase. The rotation speed difference was synchronized during the synchronization phase, and the gap was eliminated during the nonsynchronization phase. Obviously, the controls target quantity and drag force were different at each phase.

2.2. Electromagnetic Linear Actuator. Due to the enhancement in permanent magnet materials, power electronics, and control technology, the electromagnetic linear driving device is widely applied to high-speed and high-precision positioning systems since it is of simple structure and responds quickly.

The research object of this paper was a moving coil electromagnetic linear driving device. Figure 4 is the physical and structural diagram of electromagnetic linear drive. Stator permanent magnets are fixed in a certain position by arranging in a Halbach array. While effectively increasing the magnetic field strength inside the stator, it also reduces the magnetic field strength outside the stator. The energized coil winding generates motion due to the generated electromagnetic force under the action of a magnetic field. Electromagnetic linear driving device is the application of this electromagnetic conversion principle. When an external power source is applied, the mover coil is driven by electromagnetic force in the magnetic field generated by the permanent magnet. Performance indexes of electromagnetic linear driving device are shown in Table 1.

2.3. Data Collection Scheme. In order to ensure the method applicability of mover displacement estimation for electromagnetic linear driving device, it was necessary to obtain the relevant parameter signals under various working conditions as sample data. Table 2 shows the code according to the determined gearshift condition.

The measurement and control system collect the first gear to the second gear in each working condition: the data signal of current, voltage, and displacement for mover that varied with time and data signal of the transmission input shaft speed that varied with time.

3. Position Sensorless Control Method Based on Improved GA-BP Neural Network Algorithm

3.1. Principle of Indirect Displacement Detection. The electromagnetic linear driving device is a complex system in which three subsystems with circuit, magnetic, and mechanical are coupled to each other. Principle of magnetic, circuit, and mechanical can be expressed as

\[ U_C(t) = R_c I_c(t) + L_c \frac{dI_c(t)}{dt} + E_{emf}(t), \]

where \( U_c(t) \), \( I_c(t) \), \( L_c \), and \( R_c \) are electrical parameters of winding expressed as terminal voltage, current, inductance, and resistance, respectively. \( E_{emf}(t) \) is the back emf:

\[ E_{emf}(t) = B_l N_c v_c(t) = k_e v_c(t), \]

where \( B \) is the air-gap magnetic field intensity, \( l_c \) is the average effective length of a single turn of a coil conductor, \( N_c \) is the total turns, \( v_c(t) \) is the coil moving speed, and \( k_e \) is the back emf coefficient.

\[ F_m = B_l N_c k_e I_c(t) = k_m I_c(t), \]

where \( F_m \) is the driving force of the electromagnetic linear driving device and \( k_m \) is the motor constant of the electromagnetic linear driving device, which is equal to the back emf coefficient in value.

According to equations (1), (2), and (3), the mover displacement can be derived:
Figure 2: Measurement and control system structure diagram of direct-drive-type AMT.

Figure 3: Measurement and control system of the electromagnetic linear driving device test bench.

Figure 4: Physical and structural diagrams of the electromagnetic linear driving device: (a) physical diagram; (b) structural diagram. (i) End cover; (ii) coil frame; (iii) driving shaft; (iv) permanent magnet; (v) coil winding; (vi) inner magnetic yoke; (vii) outer magnetic yoke.
To the output layer using the adjusted parameters. At the same time, by adjusting the number of layers in the middle layer and the weight value of the neurons in each layer, the network output result is continuously approximated to the expected result.

For the BP neural network algorithm initialization, it is not easy to find the optimal parameters of the network and easy to fall into the local minimum value. The BP neural network was optimized by the genetic algorithm with improved selection factor to determine the weight and threshold. The operation principle of the improved GA-BP algorithm is shown in Figure 6.

The number of nodes in the hidden layer is uncertain during the process of establishing the BP neural network. Based on the established BP network, the optimal number of nodes in the hidden layer needs to be determined through the trial and error method. Figure 7 shows the process of the trial and error method to determine the optimal number of nodes in the hidden layer.

According to Figure 7, the change law of the relative error when the number of nodes in the hidden layer is increased from 3 to 300 can be obtained. It can be seen that when the number of hidden layer nodes is less than 26, the accuracy of network prediction increases with the number of hidden layer nodes; when the number of hidden layer nodes is greater than 26, the accuracy of network prediction increases with the hidden layer. The number of nodes increases and decreases; the network prediction effect is best when the number of nodes in the hidden layer is 26, and the accuracy is 94.9%.

Determining the initial model of BP neural network by the trial and error method, the optimal number of hidden layer nodes was 26. The input signal was forward transmitted, error is propagated back, and the genetic algorithm was introduced in the process of inversely adjusting the network weight and threshold:

1. Using the input hidden layer weights, input hidden layer thresholds, output hidden layer weights, and output hidden layer thresholds as the four optimization factors of the genetic algorithm. The factors to be optimized were encoded by the real number method, as shown in Table 3.

2. According to the prediction target, the fitness value of an individual was the sum of the error absolute value between the predicted value and the target value. Therefore, the fitness function was expressed as

\[ S = c \sum_{i=1}^{n} \text{abs}(ynn_i - \text{output}_i) \]  

where \(ynn_i\) represents the training output, \(\text{output}_i\) represents the target output, and \(c\) represents the fitness function coefficient.

3. The traditional selection method only preserves the excellent individuals of the population and ignores the remaining individuals. The diversity of the

### Table 1: Performance indexes of the electromagnetic linear driving device.

| Parameter                        | Value          |
|----------------------------------|----------------|
| Motion part quality (g)          | 1007.62        |
| Motion displacement (mm)         | ±12            |
| Average electromagnetic force constant | 41             |
| Rated current (A)                | 30             |
| Rated voltage (V)                | 60             |
| Rated driving force (N)          | 1230           |
| Inductance (mH)                  | 1.32           |
| Resistance (Ω)                   | 1.75           |

### Table 2: Condition code table.

| Condition code | Voltage (V) | Speed difference (r/min) |
|----------------|-------------|--------------------------|
| Condition one  | 30          | 400                      |
| Condition two  | 31          | 450                      |
| Condition three| 30          | 450                      |
| Condition four | 31          | 500                      |
| Condition five | 32          | 500                      |
| Condition six  | 32          | 550                      |

\[ x_c(t) = \int v_c(t) dt = \frac{1}{k_c} \left[ \int (U_c(t) - R_c I_c(t)) dt - L_c I_c(t) \right], \]  

where \(x_c(t)\) is the displacement of moving parts. According to equation (4), the indirect displacement detection principle of the electromagnetic linear driving device without displacement sensor control based on artificial neural network is as follows: the electromagnetic linear driving device current and voltage in the data samples were selected as the input information about artificial neural network. An artificial neural network with appropriate structure was established to make the output information as the network displacement prediction of the motor. Considering the gearshift control strategy of the measurement and control system, in phase of synchronization without displacement, the speed signal was used as the feedback value. At the same time, the rotation speed of the input shaft changes before the gearshift process. Therefore, the speed of the transmission input shaft was also taken as the input signal to improve the accuracy of network prediction results. The schematic diagram of indirect displacement detection is shown in Figure 5.

### 3.2. Algorithm Design Process.

BP neural network has strong nonlinear mapping ability, adaptive and self-learning ability, and strong fault tolerance and other characteristics, suitable for the prediction of nonlinear displacement during shifting. BP neural network is different from other networks; in that, the signal propagates forward, and the error is passed backward. In other words, when the result obtained by the output layer is different from the expected result, the error will be transferred to the reverse transfer process. After the error reverse adjustment is completed, the input signal will continue to propagate in the direction from the input layer to the output layer using the adjusted parameters. At the same time, by adjusting the number of layers in the middle layer and the weight value of the neurons in each layer, the network output result is continuously approximated to the expected result.

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where \(ynn_i\) represents the training output, \(\text{output}_i\) represents the target output, and \(c\) represents the fitness function coefficient.

3. The traditional selection method only preserves the excellent individuals of the population and ignores the remaining individuals. The diversity of the
Hidden layer neurons

0.7
0.8
0.9
1.0

Relative error

Figure 7: Process of the trial and error method to determine the optimal number of nodes in the hidden layer.

Figure 5: Indirect displacement detection principle of the electromagnetic linear driving device based on the artificial neural network.

Figure 6: Operation principle of improved GA-BP algorithm.
population was destroyed, which was easy to cause local convergence of the algorithm. This paper improved the selection operator based on the preservation of excellent individuals and proposes a new selection operation; Figures 8–11 show a four-step improved selection operation:

**Step 1.** Set the number of initial populations as 6

**Step 2.** The individuals in the population were arranged from the largest to the smallest according to the fitness value and were divided into two segments in an average order

**Step 3.** Sort the arranged individuals by parity and divide them into two segments

**Step 4.** The individuals with odd order and large fitness value were retained to the next generation, and the new population formed was the result of selection

### 4. Experiment and Discussion

#### 4.1. Offline Training Results

Sample data of each working condition were selected as training and test samples for the network and loaded into the improved GA-BP network to be trained and tested.

Figure 12 shows the prediction results of the improved GA-BP network under the condition one, and the accuracy of prediction result was 96.4%. According to Figure 12(a), there were some prediction errors at the beginning of the downshift phase. Then, there were small prediction errors at the end of the upshift first phase and at the beginning of the synchronization phase. The mean absolute error of network prediction in the end of synchronization phase and other phases was less than 0.5 mm. According to Figure 12(b), in addition to the early phase of downshift and the synchronization phase, the prediction of the remaining phase was better. The maximum absolute error value of the prediction result was 3.3 mm in the beginning of the downshift first phase. RMSE of the network was predicted to be 39.333, MAPE was 0.26%, and training time of the network was 5.981 s. Simulation results show that the gearshift time of this condition was 0.159 s from the first gear to second gear. Sample data of six working conditions were loaded into BP and improved GA-BP network, respectively, and the comparison of prediction results is shown in Figure 14.

According to Figure 14, the prediction accuracy of the improved GA-BP network was better than that of the BP network and RBF network under the same working conditions. In accuracy respects, the accuracy of the improved GA-BP was 2.2% higher than the BP network and 1.2% higher than the RBF network. Compared with the prediction results of the BP network, RMSE of the improved GA-BP network decreased by 21.8% on average and MAPE
decreased by 23.9% on average, and the discrete degree of prediction was better than that of the BP network. Compared with the prediction results of the RBF network, RMSE of the improved GA-BP network decreased by 115.5% on average and MAPE decreased by 39.6% on average, and the discrete degree of prediction was significantly better than that of the BP network. Influenced by the number of iterations, the improved GA-BP algorithm uses longer training time.

4.2. Error Analysis. Take prediction results of the improved GA-BP network under condition one as an example to analyze the source of error.

Figure 15 shows the sequence diagram of voltage, current, and predicted error under working condition 1: s-a was the phase of downshift, a-b was the first phase of upshift, b-c was the synchronization phase, and c-g was the three to six phases of upshift; the synchronization phase accounts for 67 percent of the gearshift. We combine the remaining four phases into one phase for analysis, so the whole gearshift process can be divided into the downshift phase, upshift phase, synchronization phase, and remaining phase of upshift. In the phase of downshift, DC power begins to supply energy for the electromagnetic linear driving device, this moment of voltage and current suddenly increases, and the neural network predicted has errors because the network has poor dynamic following behaviors to the data. In the first phase of upshift, as the current increases, coil velocity gradually becomes faster, resulting in a second error fluctuation at that location. Another reason for the error fluctuation in these two phases was that the sampling time is
short, only a few sample points were collected, and the neural networks were difficult to construct. At the beginning of the synchronization phase, there was a large fluctuation in current and voltage, and the reason is still unclear and will continue to study later. During the synchronization phase and remaining phase of upshift, the error only appears at the beginning, and the rest of the error was within the acceptable level.

From the analysis in Figure 15, the main prediction error occurs before the synchronization phase, and the maximum error occurs in the start time. The main reason is that the fluctuation of current and voltage leads to the deterioration of the network’s dynamic following behaviors, and the prediction is biased. However, the moment when the maximum error occurs does not affect the gearshift control strategy, which can meet the shift requirement.

4.3. Position Sensorless Control Experiment and Result Analysis. Position sensorless control tested based on electromagnetic linear driving device and measurement and control system was carried out. Determine gearshift conditions, load the improved GA-BP network that has been trained under this condition into the controller, and control system performed gearshift operations: the current and voltage of the electromagnetic linear driving device and the speed signal of AMT input shaft collected by the sensor were used as input signals to the improved GA-BP network. During the gearshift process, the displacement signal was collected by the laser displacement sensor, which was recorded at the same time, but not used as the feedback signal of the controller.

Figure 16 shows the results of the position sensorless control test for the condition one. The accuracy of the network predicted displacement result was 96.1%. The test
results showed that the controller used the displacement predicted by the improved GA-BP network as the displacement feedback signal under the condition one, which is consistent with the simulation results, the gear shift can be smoothly realized, and the shifting time used was 0.160 s. Figure 16 shows that there was a certain displacement error at the beginning of the downshift first phase and synchronization phase.

Figure 17 shows the results of the position sensorless control test of condition two. The accuracy of the network predicted displacement result was 97.1%. And test results showed that the maximum prediction error under this condition does not exceed the trigger point in the synchronization stage, the gear shift can be smoothly realized, and shifting time used was 0.168 s. It can be seen from Figure 17 that similar to the test results of condition one, there was a certain displacement error at the beginning of the downshift first phase and synchronization phase.

The position sensorless control test of conditions three to six can achieve smooth gearshift. The accuracy of the network predicted displacement result was 96.4%, 97.5%, 97%, and 96.9%, respectively. Accuracy of each working condition prediction was greater than 96%.

In the position sensorless control test of various working conditions, there were some displacement predicted errors at the beginning of the downshift first phase and synchronization phase, but smooth shifting can still be achieved. The reason was that the judging condition for starting the gearshift process in the control strategy was the rotation speed difference and the gear in which it is located. In the downshift phase, the displacement prediction error is small, and the controller determines that the gear position is in the
first gear. Then, the displacement error becomes larger but still does not exceed the trigger displacement value of the synchronization phase. In the synchronization phase, controller used the rotation speed as the feedback signal and the error of the predicted displacement does not affect the control results. Displacement prediction was better in the other gearshift phase: the predicted displacement at the beginning of the other phase can reach the actual displacement value in the time range of \( \pm 1\) ms. During each phase, the absolute error of the predicted result was less than 0.5 mm, and the controller controlled the electromagnetic linear driving device output driving force based on the predicted displacement of the feedback at each phase within the range allowed by the control strategy. In summary, the position sensorless control tested based on the improved GA-BP network can achieve smooth gearshift.

5. Conclusions

In this paper, a moving coil electromagnetic linear driving device was taken as the research object and a position sensorless control method based on the improved GA-BP algorithm was proposed. Based on measurement and control system, the position sensorless control experiment was carried out and realized the prediction of the mover displacement of electromagnetic linear driving device, and the following conclusions were obtained:

1. Based on the each working condition, by improving the selection factor of the genetic algorithm, the prediction accuracy of the improved GA-BP algorithm was all greater than 96.3%. Compared with the traditional BP algorithm, average accuracy prediction was increased by 2.2%, RMSE decreased by an average of 21.8%, and MAPE decreased by an average of 23.9%. Compared with the traditional RBF network, average accuracy prediction was increased by 1.2%, RMSE decreased by an average of 115.5%, and MAPE decreased by an average of 39.6%.

2. The controller used the displacement predicted by the improved GA-BP network as the displacement feedback signal, and the gear shift can be smoothly realized. The accuracy of the test results under various working conditions was greater than 96%, absolute error of displacement prediction was controlled within \( \pm 0.5\) mm, and average shifting time was less than 0.18 s.

According to specific application needs, through offline training and experimental verification, a position sensorless control method of electromagnetic linear driving device based on the improved GA-BP algorithm was proposed. Being applicable to a variety of moving coil electromagnetic linear driving device laid a foundation for the key technology of electromagnetic linear driving device application.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors’ Contributions

Bo Li and Wenqing Ge conceived, designed, and curated the data, developed dedicated software, and commented on the manuscript. Qiang Li and Yujiao Li analysed the data using software, and wrote the manuscript. Wenqing Ge and Cao
Tan edited the manuscript and approved the published version.

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