A Hybrid Model for Optimizing Trigger Position of Multistage Synchronous Induction Coilguns

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The launch efficiency of the multistage synchronous induction coilgun (MSSICG) is highly dependent on the trigger positions. However, due to the complex nonlinear characteristics and the dynamic coupling of the MSSICG, identifying the best trigger position is a challenging task, particularly when different mass of loads are applied. This article proposes a hybrid model that combines both data-driven and physics-driven approaches for efficiently determining the best trigger positions. A deep neural network (DNN) is employed to predict the best trigger position for a single-stage launcher. The outputs of the DNN serve as intermediate variables, which are then fed into the physics-driven model to compute the sequence of best trigger positions for the MSSICG under different load conditions. Finally, a three-stage induction coilgun is used to validate the accuracy and effectiveness of the proposed hybrid model.

Index Terms—**Multistage synchronous induction coilgun,Deep neural network, best trigger position, data- and physics-driven model**

I. Introduction

MULTISTAGE synchronous induction coilgun (MSSICG) is a novel electromagnetic launch device. Due to high launch kinetic energy, flexible load adjustability, non-contact launching capability, and excellent cold-launch performance, MSSICG has considerable application prospects across military, civilian, and industrial fields [1]. However, the launch performance of MSSICG is significantly influenced by several critical parameters. Simulations and experimental results have shown that, among these parameters, the trigger position directly affects both launch efficiency and acceleration stability [2]. Determining the best trigger position for each stage to ensure the synchronization between electromagnetic thrust and projectile motion can significantly improve the energy conversion efficiency and acceleration effect of MSSICG. However,the process of determining the best trigger position is tedious and computationally expensive due to the step-by-step tuning required for each stage.

One of the key advantages of the MSSICG is its ability to adaptively launch projectiles of different masses by adjusting the excitation current. However, traditional methods for determining the trigger position lack the adaptability required to handle different load conditions. With the rapid advancement of artificial intelligence, neural networks have gained significant attention in the design and optimization of MSSICG, due to their strong nonlinear mapping capabilities and efficiency in modeling complex relationships. In the publications [3] and [4], deep neural networks (DNN) and multilayer neural networks (MLNN) are utilized, respectively, to perform sensorless prediction of projectile position. This approach enables real-time position monitoring and introduces a novel sensorless control triggering scheme.

Based on deep neural networks and the physical principles of the MSSICG, this paper proposes a hybrid model that facilitates the determination of the optimal sequence of trigger positions under different load conditions. Compared to purely data-driven models, this hybrid approach enhances physical interpretability and generalization capability while reducing reliance on large-scale training data. Furthermore, the hybrid model enables real-time prediction, significantly improving the efficiency of searching for the best trigger positions.

II. Problem Description and Model Architecture

A. Determine the optimal trigger position

According to the CFM (current filament method), the equivalent circuit model of MSSICG is shown in Fig. 1. Based on Kirchhoff's laws and the principle of virtual work, the control equations of the launch system can be expressed as:

$$\begin{cases} \boldsymbol{U} = \boldsymbol{R}\boldsymbol{I} + \boldsymbol{L}\dot{\boldsymbol{I}} + v\dfrac{\mathrm{d}\boldsymbol{M}}{\mathrm{d}z}\boldsymbol{I} + \boldsymbol{M}\dot{\boldsymbol{I}} \\ \boldsymbol{F} = \dfrac{1}{2}\boldsymbol{I}^T\dfrac{\mathrm{d}\boldsymbol{M}}{\mathrm{d}z}\ \boldsymbol{I} \end{cases} \tag{1}$$

where $\boldsymbol{U}$ and $\boldsymbol{I}$ are the column vectors of dimension $m+n$, representing the voltage and current vector of the current filaments and driving coil circuits, respectively. $\boldsymbol{R}$ and $\boldsymbol{L}$ are the $(m+n)\times(m+n)$ diagonal matrices, representing the resistance and self-inductance of the current filaments and driving coil circuits, respectively. $\boldsymbol{M}$ is the $(m+n)\times(m+n)$ matrix, representing the mutual inductance either between the current filaments or between the current filaments and the coils. $\boldsymbol{F}$ is the column vector of dimension m, representing the force on the current filaments.

According to (1), it can be seen that the highly nonlinear relationship between electromagnetic force and system parameters in the induction coilgun system, as well as the significant influence of load variability on determining the best trigger position. The complexity and dynamic nature make identifying the best trigger position extremely challenging. Therefore, this article leverages the ability of deep learning models to capture the dynamics of this complex nonlinear system, enabling accurate prediction of the optimal trigger positions.

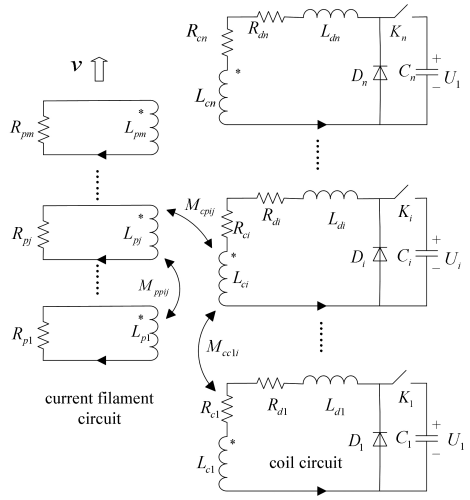


Fig. 1. Equivalent circuit model of multistage synchronous induction coilgun

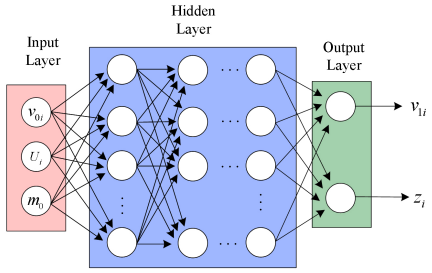


Fig. 2. Block diagrams of the hybrid model

B. The Architecture of hybrid model

Fig. 2 illustrates the block diagram of the data-driven model, which is implemented using a DNN framework. The input features to the DNN include the initial velocity v_{0i}, energy storage capacitor voltage U_i, and load mass m_0—parameters that influence the trigger position of a single-stage coil i. The DNN models the complex nonlinear process of determining the optimal trigger position for a single-stage coil, generating the best trigger position z_i and the exit velocity v_{1i} as target variables. The data-driven model can be abstracted as follows:

$$(z_i, v_{1i}) = \mathcal{F}(v_{0i}, U_i, m_0) \tag{2}$$

where $\mathcal{F}$ represents the nonlinear mapping learned by the DNN framework.

The hyperparameters of the DNN are optimized using Optuna, which efficiently performs hyperparameter tuning through adaptive sampling and pruning strategies. Once the architecture of the data-driven model $\mathcal{F}$ is determined and the model is trained, it is then integrated into the physics-driven model to calculate the sequence of the best trigger position $[z_1, z_2, ..., z_n]$ for the n-stage synchronous induction coilgun.

III. Result and Analysis

In this study, the current filament model is used to generate the training data, and the Latin hypercube sampling (LHS) technique is employed to ensure that sample points are uniformly distributed across the variable space. The ranges of the feature variables v_{0i}, U_i, and m_0 are set as $[0\,\mathrm{m/s}, 100\,\mathrm{m/s}]$, $[3000\,\mathrm{V}, 10000\,\mathrm{V}]$ and $[1\,\mathrm{kg}, 10\,\mathrm{kg}]$, respectively. The dataset is partitioned into a training set, validation set and test set, with proportions of 70%, 15%, and 15%, respectively.

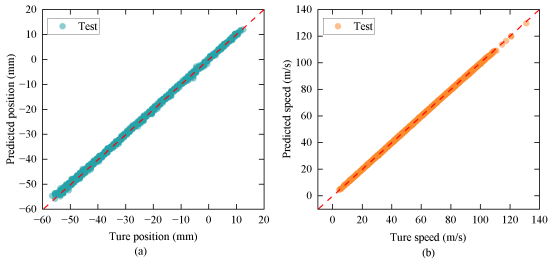


Fig. 3. (a) Scatter Plot of Predicted vs True Position. (b) Scatter Plot of Predicted vs True Speed

TABLE I
Comparison of Results Between the Current Filament Model and the Hybrid Model

	CFM		Hybrid Model		Error	
stage	v_t (m/s)	z_t (mm)	v_p (mm)	z_p(mm)	ε_v (%)	ε_z(%)
1	18.95	9.5	18.84	9.2	0.58	3.16
2	34.13	-8.5	33.81	-8.75	0.94	2.94
3	46.81	-21.5	46.30	-20.9	1.09	2.40

The model processes 256 samples per iteration. After the hyperparameter optimization, the architecture of the final DNN model consists of four hidden layers with CL: $97 \rightarrow 100 \rightarrow 82 \rightarrow 90$. The prediction results of the model are shown in Fig. 3. The predicted data points are closely aligned with the diagonal $y = x$, and the mean absolute errors (MAE) of the predicted trigger position and exit velocity are 0.3794 mm and 0.2501 m/s, respectively. These results demonstrate the high predictive accuracy of the model in estimating both the velocity and the optimal initial position.

The DNN model is then integrated with the physics-driven model to predict the sequence of the best trigger positions for a three-stage coilgun with a 5 kg payload and a capacitor voltage of 8000 V. As shown in Table I, the calculation results indicate that the prediction error of the hybrid model, compared to the step-by-step search results, is less than 5%, demonstrating its capability to accurately and efficiently predict the trigger positions of the MSSICG.

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