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Research Article

Self-Coupling Black Box Model of a Dynamic System Based on ANN and Its Application

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The black box model of a dynamic system usually consists of just input and output. There is no correlation or coupling between the input and output. This paper proposes a self-coupling black box model method to realize the coupling between its input and output by introducing "virtual variables" to the black box model of a dynamic system considering the advantages of artificial neural network (ANN) in the system. The ANN is used for black box modeling. The modeling process of the self-coupling black box is illustrated through the simulation models and simulation analysis of the particle settlement process and the Unmanned Undersea Vehicle (UUV) launching process. By comparing its result with the result of the standard black box model, the advantages and disadvantages of the self-coupling and standard black box models in the calculation of accuracy are analyzed.

1. Introduction

The black box models are developed by measuring the data of the system input and output and fitting a mathematical function to the data. The development of black box models does not require the understanding of the system physics, and they have high accuracy compared to the physics-based models though they suffer from poor generalization capabilities [1]. A nonlinear black box structure for the dynamic system is a model structure constructed to describe the nonlinear dynamics [2]. The nonlinear structures can be seen as a concatenation of mapping the observed data to a regression vector and nonlinear mapping of the regressor space to the output space [3].

At present, the research on modeling methods of the black box model mainly focuses on accurately realizing the mapping relationship between input and output. In order to solve the specific engineering problems, many scholars have adopted a variety of methods to build the black box model, such as autoregressive public model (ARX), transfer function model (TF), state space model (SS), and output error model (OE) [4–8]. Research studies on black box modeling methods mainly focus on accurately realizing the implicit relationship. There is a lack of research on the correlation between the input and the output. System variables that have representational meaning are introduced in the black box model. These variables are both input and output (self-coupling) variables. However, in the calculation of the black box model, the actual input does not contain this variable. A variable "virtual" exists in the system that can generate output as an analysis parameter to observe the operation of the system.

In general, the study of dynamic system identification is concerned with its operation law. The analyzed data is the time series of the system. As an alternative method of regression analysis, the artificial neural network (ANN) can be used to identify the parameters of the dynamic system and build models. ANN, which simulates the human nervous system, is a powerful method to solve regression and classification problems [9, 10]. ANN has been successfully applied for the nonlinear modeling of time series [11–19]. It has the ability to model complex nonlinear relations in data without any prior assumptions about the nature of such relations [20]. The nonlinear properties and self-learning and adaptive abilities of the neural network method ensure strong approximation in nonlinear mapping. This method can accurately simulate the input-output relationship of the system and provide a reliable and precise model for the nonlinear system. Moreover, the ANN does not need to know the characteristics of the relationship between dependent and independent variables, which is in sharp contrast to regression analysis. In addition, the ANN can be used for online identification and a more effective real-time simulation analysis of the system. ANN is widely used in the fields of pattern classification, function approximation, and trend prediction as well [21, 22]. Therefore, after selecting the input and output of the system, this research uses the ANN as the black box modeling method.

The remainder of this paper is organized as follows. Section 2 introduces the principle and modeling process of the self-coupling black box model. Section 3 lists two specific application cases. In Section 3.1, the motion modeling and prediction of the settling process of spherical particles are introduced. Section 3.2 presents two black box models used in this study to calculate the velocity of a ballistic body and torque of the launching pump. The conclusions drawn from research work are presented in Section 4.

2. Principle of Self-Coupling Black Box Model and Modeling Method

2.1. Principle of Self-Coupling Black Box Model. The system identification black box modeling requires measurement of input-output data of the dynamic system, selection of model structure, and estimation of model parameters. When building the self-coupling black box model of a dynamic system, it is necessary to analyze the relationship between the variables in the system. The variable with the highest degree of correlation with other variables is regarded as the key variable. Consequently, the functional relationship between other variables and key variables in the system is analyzed to determine whether it contains the differential or integral of key variables. The integral or differential quantities are introduced in the black box model as "virtual quantities." The key variables and "virtual quantities" are considered as the output and input of the model, respectively. In addition, the self-coupling black box model also includes other necessary input and output quantities of the system. The biggest difference between the self-coupling black box model and the standard black box model is that more input quantities are involved in the trained model through virtual quantities, and the observation data of virtual quantities ignored in the standard black box model is also involved, which may help to improve the stability of the self-coupling black box model.

To further illustrate the principle of the self-coupling black box model, a system with four variables is illustrated [23] which includes one input variable $A_1(t)$ and three system variables $X_1(t)$, $X_2(t)$, and $X_3(t)$. $X_1(t)$ is the key variable and $X_2(t)$ and $X_3(t)$ are the integral and differential quantities of $X_1(t)$. Therefore, $X_2(t)$ and $X_3(t)$ are virtual quantities, $A_1(t)$ is the input, and $X_1(t)$ is the output of the black box model. The required black box model is shown in Figure 1. Compared with the self-coupling black box model, the standard black box model usually has only $A_1(t)$ and $X_1(t)$ as input and output, respectively; in model training process, $X_2(t)$ and $X_3(t)$ are ignored.

The simulation model of the self-coupled black box model is shown in Figure 2.

2.2. Modeling Process. The modeling process of the self-coupled black box model is shown in Figure 3, which consists of five steps:

(1) The variables of the system are analyzed, and the key and virtual variables are determined. In addition, to ensure the accuracy of the model, the input variables need to be as complete as possible.

(2) The virtual variables and input variables are used as input and the key variables contain the output of the model.

(3) According to the self-coupling black box model, distinct test results are selected to fit the neural network model (the learning sample may be adjusted according to the results in the fourth step, i.e., different test data are adopted). The fitting method can also be established by the polynomial method or other methods and is not limited to ANN.

(4) The results of self-coupling black box model calculation are checked to determine if they match the fitted experimental results. If the result is not precise, steps 2, 3, and 4 are repeated, whereas if they meet the requirements, the next step is executed.

(5) Other test data are used to verify the accuracy of the self-coupling black box model. If the result is not precise, steps 2, 3, 4, and 5 are repeated, and thus, the self-coupling black box model is built.

3. The Application Case

3.1. Prediction of Particle Sedimentation Process. Particle sedimentation is a classic problem in both solid and liquid phases, which occurs in several industrial fields or nature as liquid-solid fluidized bed and secondary sedimentation tank. When high-density spherical particles freely fall from the initial static state into water, the ball is first accelerated by gravity. Next, the particle velocity increases, followed by the falling resistance. The acceleration gradually decreases and eventually the gravity, buoyancy, and resistance acting on the particle attain equilibrium, and the particle moves with uniform speed. For particles with different diameters, gravity, buoyancy, and resistance affect each particle differently. Therefore, the particle sedimentation process varies. Many scholars have conducted several related research analyses using CFD (Computational Fluid Dynamics) to solve the particle sedimentation problems [24–29]. However, CFD analysis is time consuming, whereas the prediction of results through limited data is time efficient. Therefore, this paper explains the implementation of the coupling model using the partially known diameter of steel

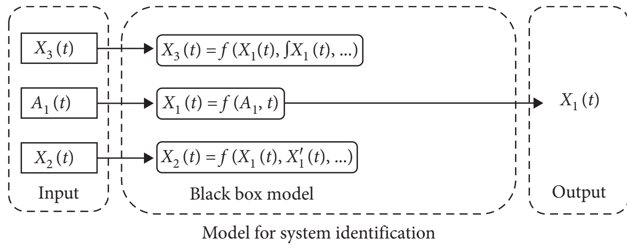


Figure 1: Dynamic system identification model.

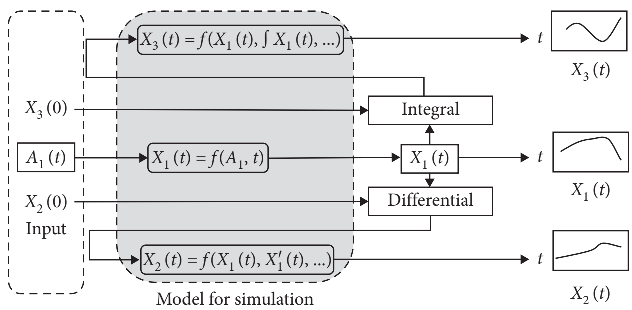


Figure 2: Dynamic system simulation model.

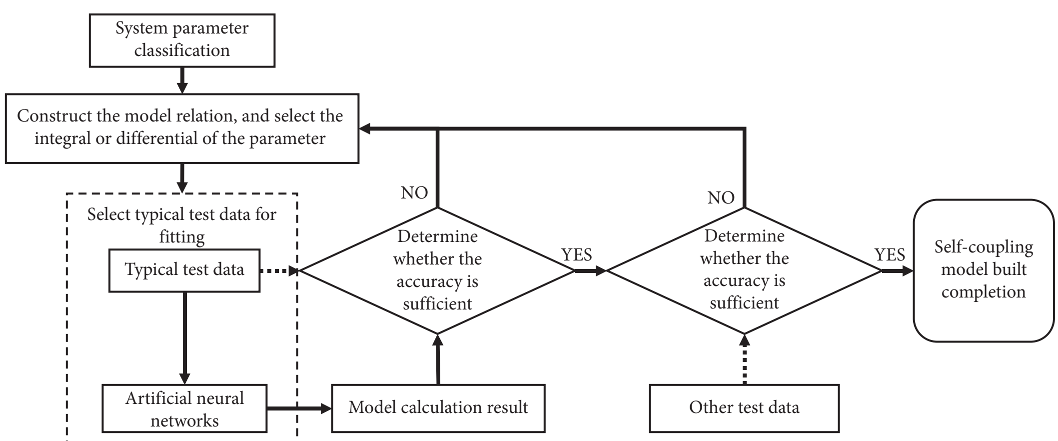


Figure 3: Flow chart of the self-coupling black box model.

ball to predict the result of particle sedimentation of particles with different diameters.

First, the settlement process data of steel ball (density 7800 kg/m3) with diameters 2 mm, 3 mm, 4 mm, 5 mm, 6 mm, 7 mm, and 8 mm were obtained through CFD analysis. The ultimate settlement velocity of spherical particles with diameters 2 mm, 3 mm, 4 mm, and 5 mm was verified through experiments, and the results are shown in Table 1. v_e is the ultimate settlement velocity obtained by the experiment and v_c is the ultimate settlement velocity calculated through CFD analysis.

Next, the variables related to the settlement process of steel balls are analyzed and the appropriate key variables and other input and output variables are selected. The variables of the self-coupled black box model include velocity $v(t)$ of the steel ball and displacement $y(t)$, which is the degree of free movement in the vertical direction when a high-density particle falls. The input variable includes the particle diameter D. Because this variable does not change with time, it is necessary to take time as input variable. In addition, the settling velocity and displacement of steel balls with diameters 2, 3, 4, 6, 7, and 8 mm are taken as input variables. A learning sample of neural network is shown in Figure 4. Compared with the self-coupling black box model, the standard black box model does not introduce the virtual quantity $y(t)$. It only takes t, D, and $y(t)$ as learning samples of the neural network, as shown in Figure 5.

The neural networks in Figures 4 and 5 adopt the cascade-forward neural network model with N neurons (Figure 6). The values of N are 9, 12, 15, 18, and 21. The training method adopts the updated values of weight and bias according to the Levenberg–Marquardt optimization

Table 1: Comparison between the ultimate settling velocity of different spherical particles with experimental results.

D (mm)	v_e (m/s)	v_c (m/s)	Error
2	0.6117	0.6032	−1.39%
3	0.7932	0.7626	−3.86%
4	0.9234	0.9072	−1.75%
5	1.0542	1.093	3.68%

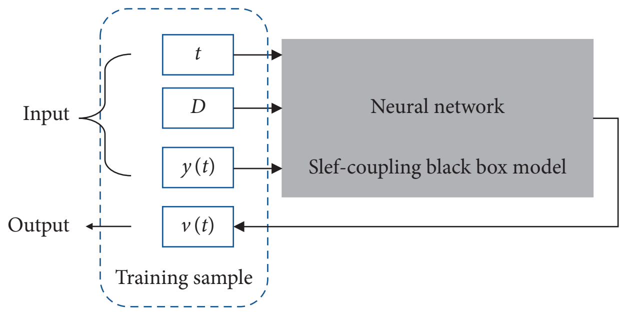


Figure 4: Schematic diagram of self-coupling black box model architecture.

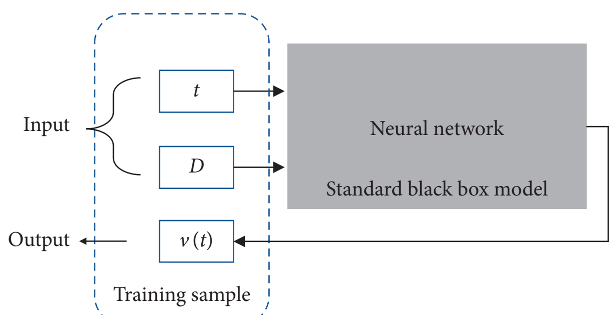


Figure 5: Schematic diagram of standard black box model architecture.

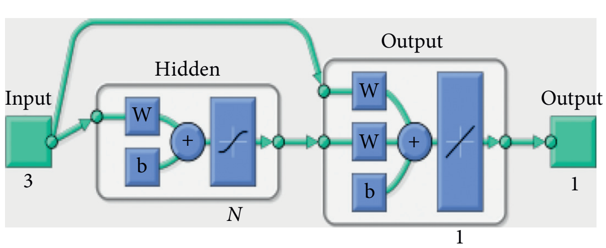


Figure 6: Sketch of the cascade-forward neural network.

method. Seventy percent of the data is selected as training data, 15% as model validation data, and the remaining 15% as test data. The maximum number of training repetitions is 10,000, the training accuracy is 1e−7, and the training speed is 0.5.

After the training of neural network, the neural network model is put into the simulation model of particle settlement process (Figures 7 and 8).

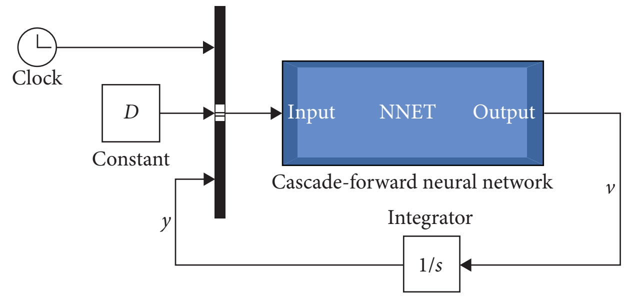


Figure 7: Particle settlement process simulation model based on the self-coupled black box model.

The standard and self-coupling black box models were used to predict the settlement velocity of spherical particles with a diameter of 5 mm. The results of the calculation are shown in Figure 9.

The average error (AE) and other performance indicators such as the root mean square error (RMSE) and average absolute relative error (AARE) were determined for the black box models. These performance indicators are listed in Table 2. According to the error analysis in Table 2, the self-coupled black box model has higher accuracy and better stability for calculating different quantities of neurons.

3.2. Interior Ballistic Prediction. UUV (unmanned underwater vehicle) is widely used in deep-sea exploration and survival risk such as underwater operation, which can generally be set in the water or underwater. The advantages of underwater release severe sea state can be avoided, but release of UUV underwater conditions need to rely on the submarine weapon launch system to achieve. Air turbine pump (ATP) launch system (Figure 10) is the navy submarine in active service in the world's most advanced hydraulic balance type deep-water launcher [30]. With its large launching depth, small volume, light weight, strong versatility, high utilization of launching energy, and low launching noise, the ATP launching system is suitable for installation on various types of submarines. The principle of ATP is that the launcher pump pushes seawater into the launcher tube to push the projectile body out of the tube, so the underwater launching process of projectile is a complex fluid structure interaction (FSI) problem. If a simple and efficient interior ballistic model can be constructed, it will be of great significance to the design of interior ballistic parameters and the safety analysis of launching. Therefore, this paper intends to build the interior ballistic simulation model using as few as possible inputs.

The ATP launch systems analyzed in this paper are conducted with the same projectile and the same initial condition. Therefore, the only difference of the internal ballistic model is the rotation speed of the launch pump. The interior ballistic model of ATP launch systems are established by using the self-coupling black box model method and the standard black box model, respectively (Figure 11). The only difference between the two models is that the input of the self-coupling black box model includes the virtual

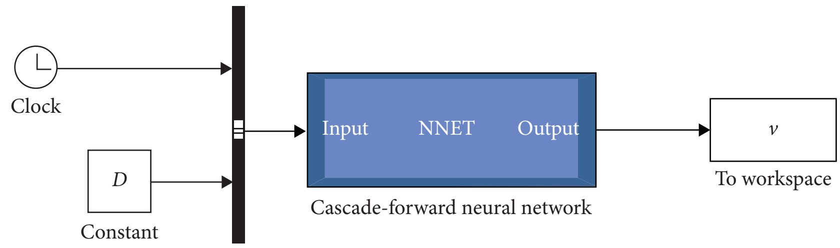


Figure 8: Particle settlement process simulation model based on the standard black box model.

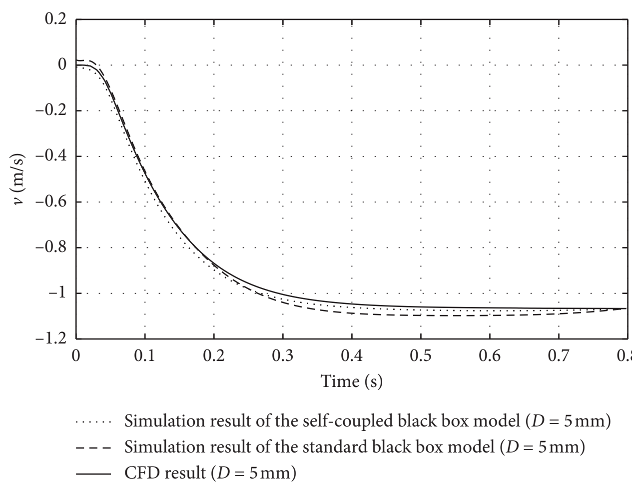


Figure 9: Comparison of settlement velocity curves of spherical particles obtained by different black box models.

Table 2: Overall error performance comparison using different performance indicators.

	The self-coupling black box model $D = 5$ mm, velocity: v (m/s)			The standard black box model $D = 5$ mm, velocity: v (m/s)		
	AE	RMSE	AARE	AE	RMSE	AARE
9	−1.64E−05	6.28E−02	1.54E−03	−2.36E−05	5.00E−03	2.21E−03
12	−1.06E−05	6.99E−03	9.92E−04	5.80E−05	5.85E−02	5.44E−03
15	2.71E−06	2.00E−02	2.54E−04	−3.94E−05	2.42E−02	3.70E−03
18	3.94E−05	2.30E−02	3.69E−03	6.12E−05	1.84E−01	5.74E−03
21	4.20E−05	1.53E−02	3.94E−03	6.96E−05	2.27E−02	6.53E−03

Note. The colored cells correspond to the best values of AE, RMSE, and AARE.

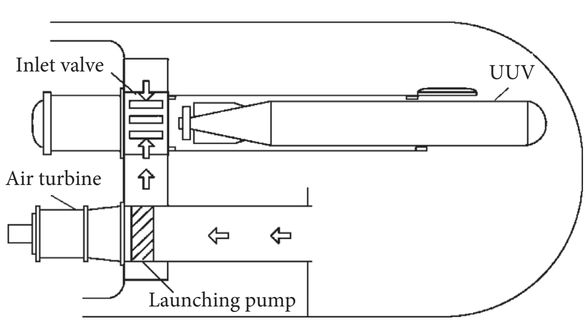


Figure 10: Schematic of the ATP launch system [30].

quantity the projectile displacement $x(t)$. There are two output quantities in both the black box models, where $u(t)$ is the velocity of the projectile and $T(t)$is the torque of the launch pump.

In each interior ballistic model, the neural network module uses the cascade-forward network. In order to compare the effects of different number of neurons, the numbers of neurons N for each model is set as 10 and 20 respectively. Six groups of internal ballistic test data (No. 1 to No. 6 test data) are used as learning samples in training. The training method updates weights and biases according to Levenberg–Marquardt optimization method. The data were split into three parts: 70% is selected as training data; 15% is used as model validation data; and 15% is used as test data. The maximum epoch of training is set as 5000. The threshold accuracy is set as 1e-8 and the training rate is chosen as 0.2. The modeling process of the black box models can be described as a flow chart (Figure 12), where $\delta_u(i)$ and $\delta_T(i)$ denote the average absolute relative error (AARE) of the simulation calculation results of projectile velocity and

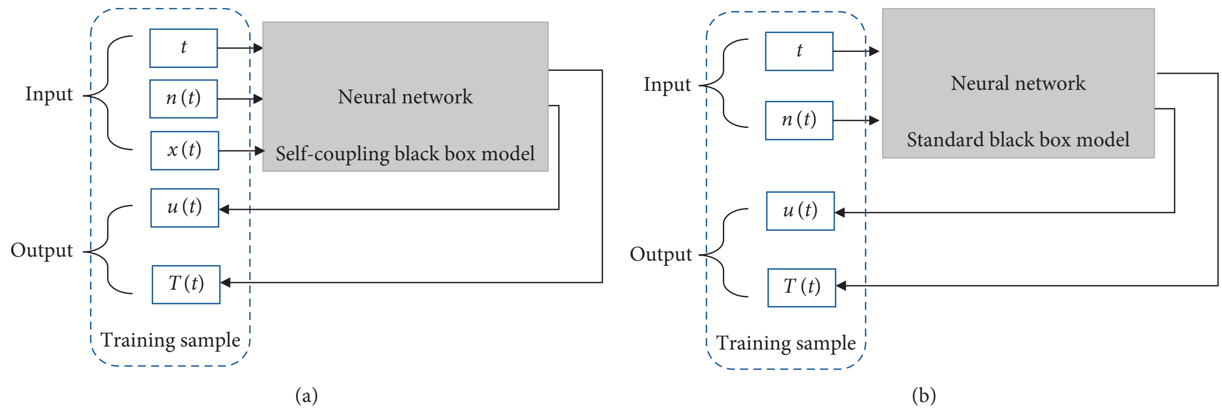


FIGURE 11: Schematic diagram of black box model architecture for interior ballistic. (a) The self-coupling black box model. (b) The standard black box model.

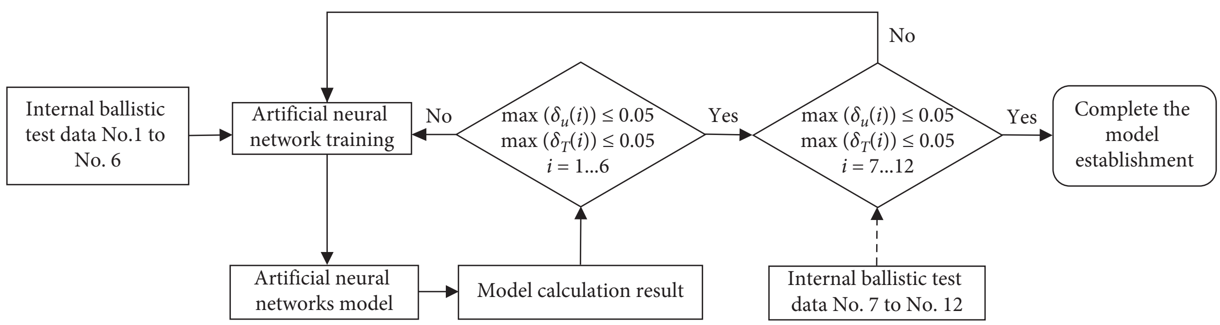


FIGURE 12: Flow chart of the black box models.

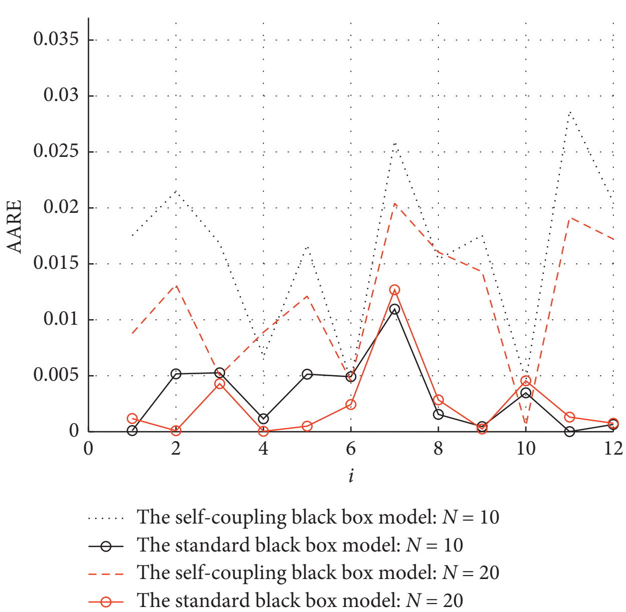


FIGURE 13: AARE for the torque of the launch pump.

launch pump torque, respectively, and i is the number of interior ballistics.

After several iterations, the AARE of $T(t)$ and $u(t)$ of the two interior ballistic black box models are less than 0.05, as shown in Figures 13 and 14.

When $N = 10$, the simulation results of the self-coupling black box model and the standard black box model are compared with available experimental results, as shown in Figure 15. It can be seen from the calculation results that the projectile velocity obtained by the two black box models is close to the experimental results. However, the torques calculated by the standard black box model from No. 8 to No. 10 were significantly different from the experimental results, while the projectile body velocity and launch pump torque calculated by the self-coupling black box model were in good agreement with the experimental results.

Figure 16 shows the interior ballistic calculation results from No. 7 to No. 12 (except the training sample) when $N = 20$, and it can be seen that the results obtained by the standard black box model become significantly worse as the number of neurons N increases, compared with the self-coupling black box model, and the results of projectile velocity still fluctuate more dramatically. In addition, it should be noted that when $N = 20$, the torque results obtained by the self-coupling black box model with trajectories of No. 8, No. 9, No. 10, and No. 11 also become worse. This indicates that the number of neurons has a certain influence on the stability of the results of the two types of interior ballistic black box models.

In general, when the interior ballistic black box model is constructed with the same error standard, the interior ballistic results of the self-coupling black box model are better than those of the standard black box model, and the

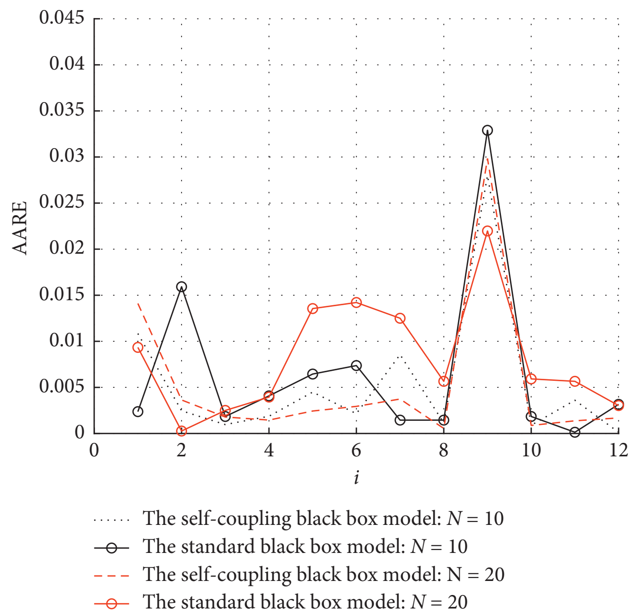


Figure 14: AARE for the velocity of the projectile.

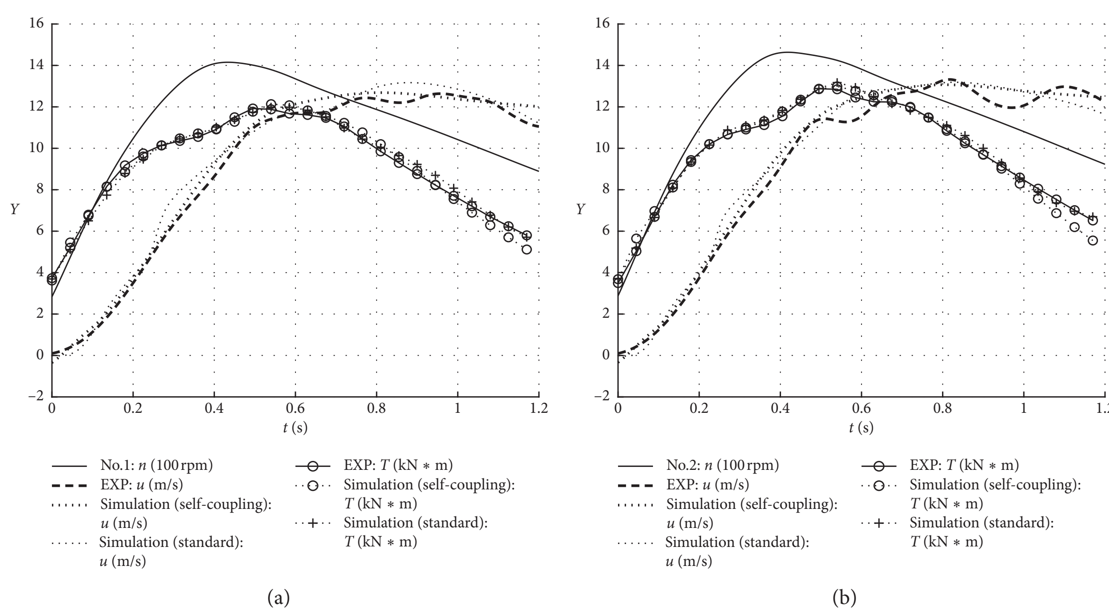
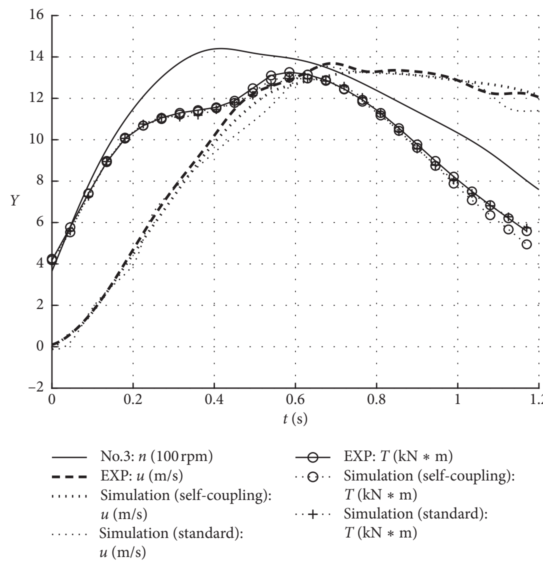
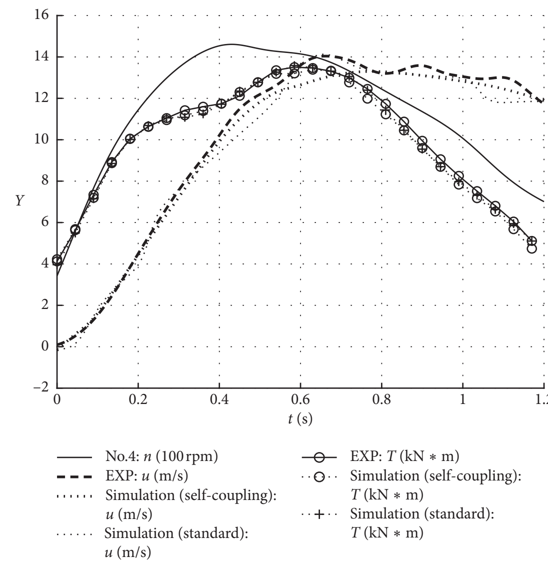


Figure 15: Continued.



(c)



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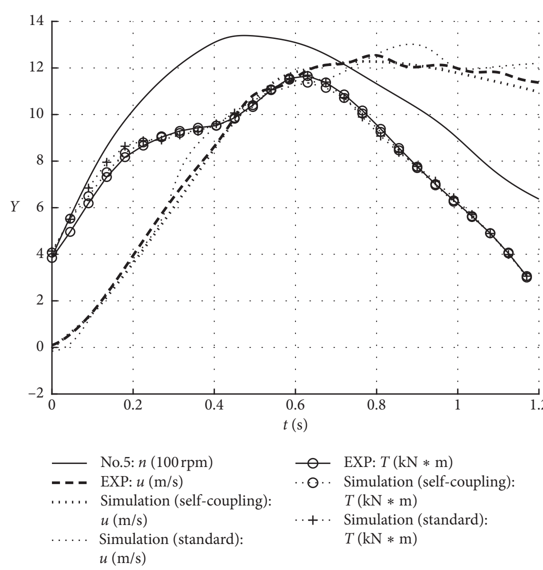

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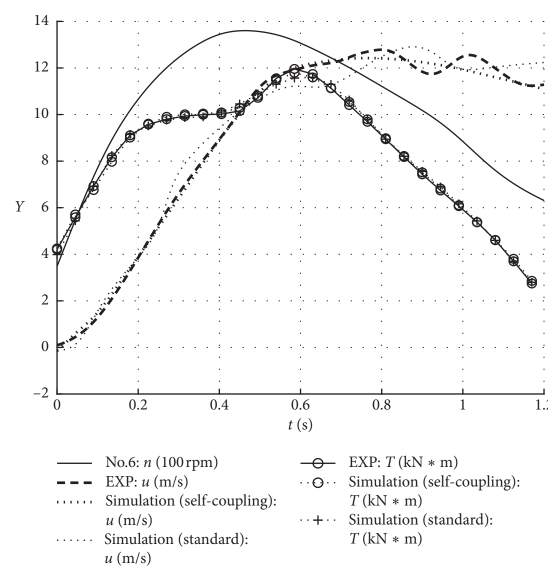

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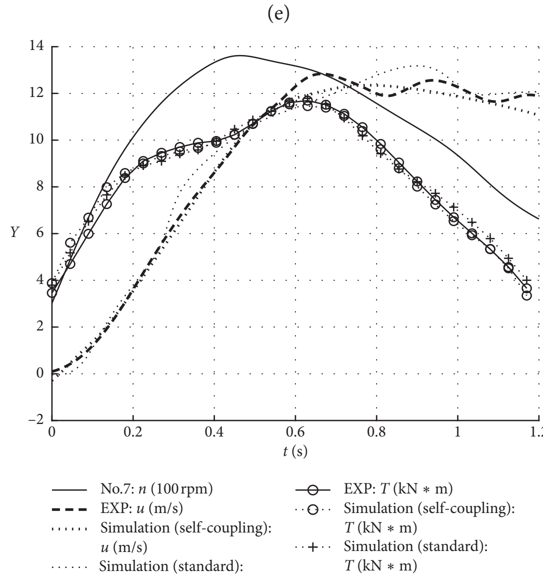

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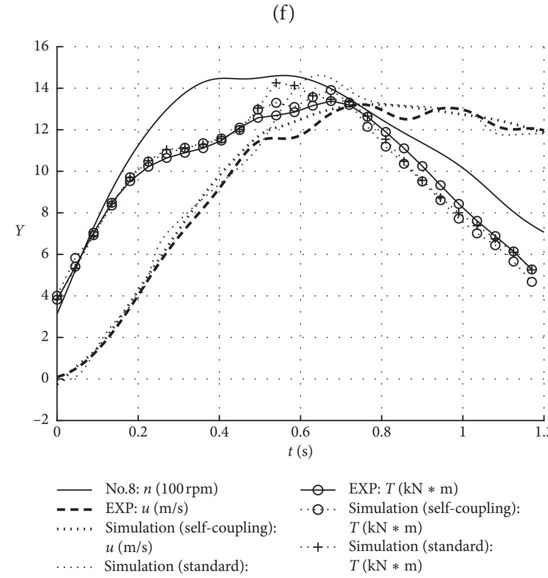

(h)

Figure 15: Continued.

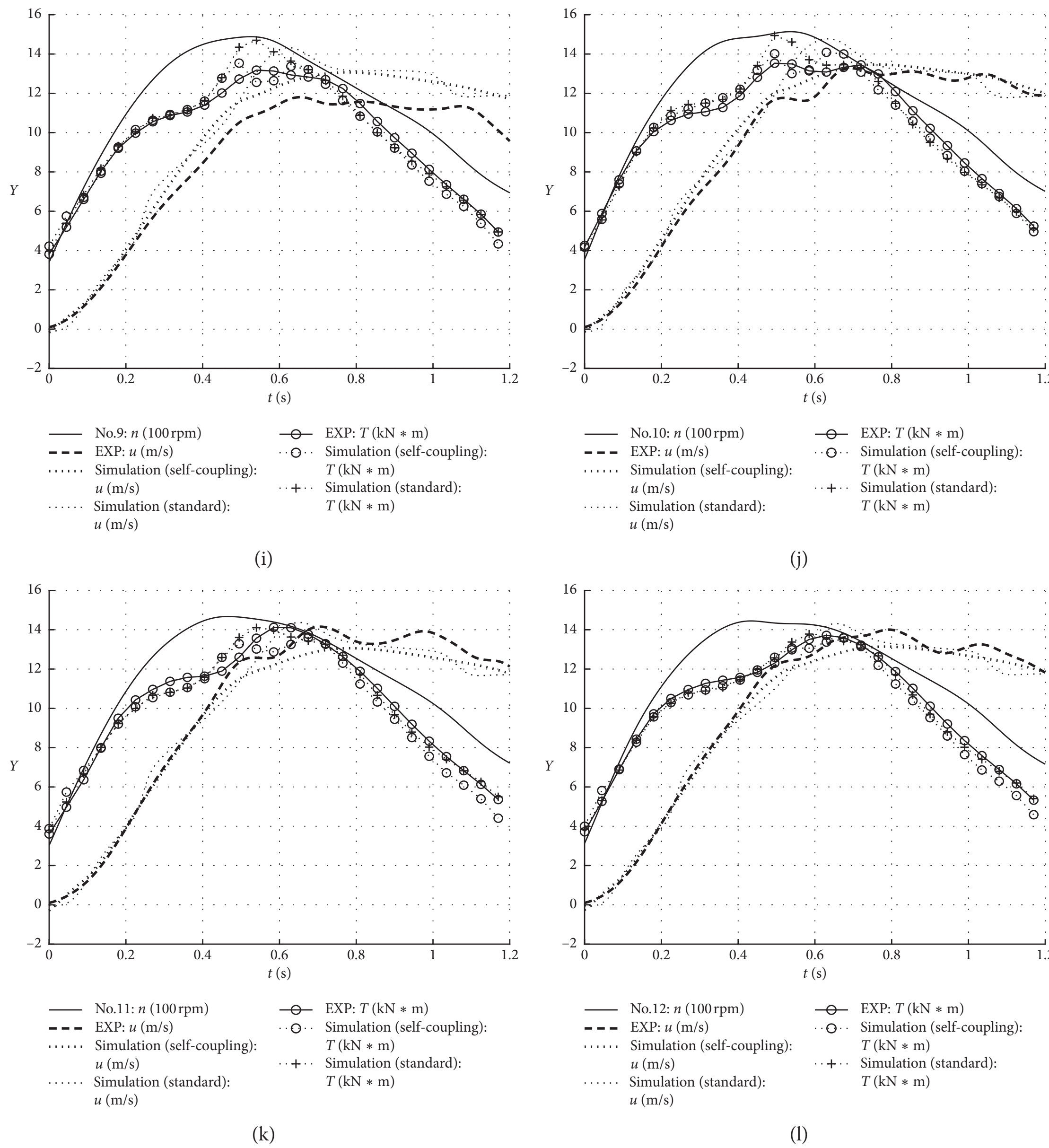

Figure 15: Comparison of the ballistic calculation with different black box models ($N = 10$).

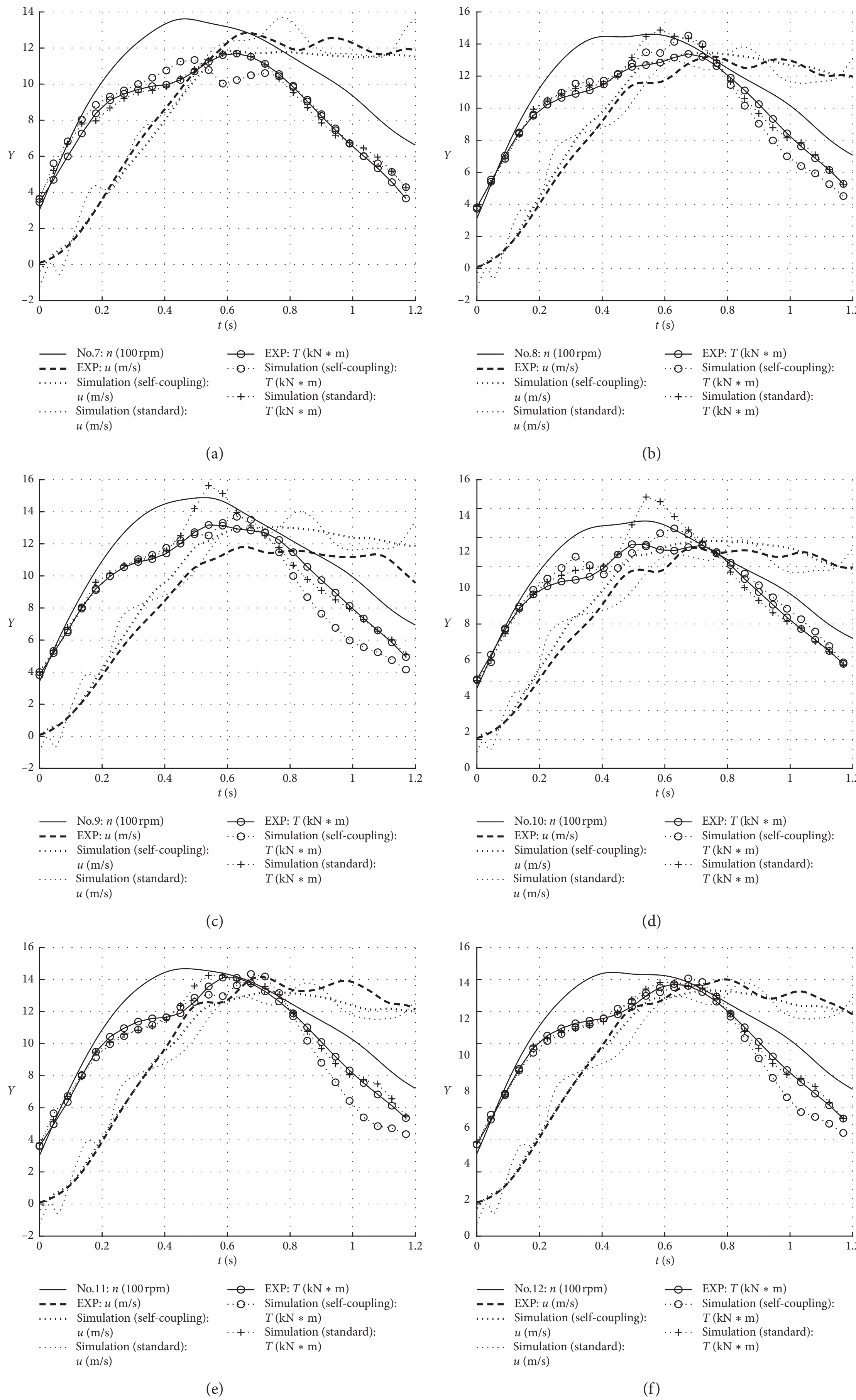

Figure 16: Comparison of the ballistic calculation with different black box models ($N = 20$).

stability of the self-coupling black box model is better than that of the standard black box model.

4. Conclusion

This paper presents a self-coupling black box modeling method for a dynamic system. This method first classifies the system parameters according to the characteristics of the dynamic system and then manually selects the parameters to formulate the hypothesis model. Finally, it adopts the ANN to construct a definite model and verify its result.

In this paper, two application cases are given, which are motion modeling and prediction of spherical particle settlement process and modeling and trajectory prediction of the internal ballistic system of the ATP launch system. The application results show that this method is simple and efficient compared with other systems identification methods and can predict the dynamic system operation process based on limited data samples. Compared with the standard black box model method, the self-coupling black box model method can obtain more accurate and stable simulation results.

Data Availability

The experiment data used to support the findings of this study have not been made available because the relevant data related to trade and technical secrets and other aspects of the content are not authorized by the relevant units to disclose.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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