HYDRAULIC PILE HAMMER SURROGATE MODEL BASED ON PHYSICS-INFORMED NEURAL NETWORK

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ABSTRACT

The high fidelity digital model of hydraulic pile hammer is able to predict the energy conversion rate of hydraulic system under the specified controller parameters, and guide the matching process of controller parameters and construction conditions. Using neural network to fit the calculation results of simulation software can greatly reduce the calculation cost of prediction process. However, the unexplained feature of neural network output increases the application risk of this method. Based on the classical theory of physics-informed neural network (PINN), a PINN method based on inequalities is proposed in this paper. Based on this method, a physics-informed surrogate model network (PISMN) oriented to the simulation process of hydraulic pile hammer was constructed. It is proved that this method can constrain the output of the surrogate model, improve the stability of the training process, and the median prediction deviation of the prediction results was reduced by 53.0% in the validation set with perturbation.

Keywords: Hydraulic piling hammer, Proxy model, Neural networks

1. INSTRUCTIONS

Through the high fidelity digital simulation model of hydraulic hammer, the energy conversion rate of hydraulic system of the pile hammer can be calculated. With the help of the calculation results, the post-processing program can match the control parameters of the pile machine with the working conditions to maximize the energy conversion efficiency. However, the application of this method is limited by the tight computing power in pile hammer equipment. Therefore, it is necessary to generate a surrogate model, which should meet the following conditions: perform accurate calculations and replace simulation software, able to calculate the energy conversion rate of the hydraulic system in the construction process of the hydraulic pile hammer, and operate efficiently in the equipment with limited computing power.

There are lots of kinds of surrogate model, including polynomial response surface (PRS), Support vector regression (SVR), Radial basis functions (RBF), Kriging models, artificial neural networks (ANN), etc. By encoding the simulation database and storing it in the computing power constrained device, and using the traditional surrogate model, it is a method to approximate the prediction results of the simulation model. However, this method has the following shortcomings: it can not use the historical data of hydraulic piling construction process to correct the prediction results. Among those above methods, the surrogate model based on neural network can solve the above problems through reasonable structure design. Artificial neural network method has been widely used in the recent research of surrogate model because of its advantages in computing complex problems [1]. Compared with other surrogate models, benefiting from its iterative learning mechanism, this method has the characteristics of high calculation accuracy and strong robustness. However, this method has the following shortcomings: lack of reasoning and causality expression ability, unable to explain the reasoning process of decision-making, etc. In order to solve the above problems, the researchers proposed to use the physics-informed method to generate the neural networks to solve the problem, and the method has been applied in many fields.

The physics-informed neural networks (PINN) was first proposed by Raissi et al., and has been introduced in several subsequent paper [2]. The research follows an earlier idea of using the laws of physics to constrain neural networks. In the classical PINN study, those previous research results [3] were combined with deep neural networks to overcome the limitations of the traditional partial differential equations (PDE) solver, so as to solve those more complex problems. In addition, the study of Arnold et al. [4] also proved that this method is able to solve the problem of poor generalization ability of neural network caused by small amount of training sample data or insufficient sampling.

However, it becomes difficult to apply PINN when the relevant parameters in the physical equation are time-varying or cannot be accurately measured for some reasons. At present, in the researches of controllers using physics-informed neural network, the physical background of the controlled object is certain, which can be described systematically by relative differential equations or partial differential equations. Therefore, the related research of PINN in complex systems or other systems with insufficient prior knowledge still needs further research.

2. ALGORITHM

2.1. Surrogate model overview

When the environmental factors of hydraulic pile hammer are determined, the efficiency of hydraulic system of pile hammer can be predicted by simulation software. In order to solve the problem caused by high computational power requirement, the surrogate model based on neural network is proposed to replace the simulation model. The surrogate model in this paper is mainly used to predict the time of reciprocating movement cycle of pile hammer. According to the calculation results, the parameters such as the number of hammer strikes per minute and the energy conversion rate of the pile hammer hydraulic system can be indirectly calculated. And the calculation results will also be used to optimize the controlling parameters of pile hammer during the construction process.

The following figure (**Figure 1**) shows the basic structure of the surrogate model, which is named physics-informed surrogate model network (PISMN) in this paper. The output of the model is the period of a reciprocating movement of the pile hammer, and the symbol is t. Input vector of the model is $\{s, p_a, r\}$, including the vector of controlling parameter during construction process(marked as s), measurable physical parameter vector of the pile machine(marked as p_a) and the vector of historical data during the pile hammer operation (marked as r). And the vector of controlling parameter during construction process include three indexes: the input power of the hydraulic pump (marked as P), the delay time(marked as t_d) before lifting the hammer, that is, the time that hammer stay on the pile anvil after the impact, and the lifting height of the hydraulic pile hammer (marked as h).

For the pile hammer hydraulic system, after the hammer impacts the pile anvil, the movement direction of the hydraulic medium flowing in the cylinder changes, and then the pressure and flow in the hydraulic system fluctuate. In addition, the reaction force may cause the hammer to bounce upward and further aggravate the fluctuations of pressure and flow. Studies have shown that large amounts of energy are often lost when valves switch between the two states, and solutions such as soft switching have been proposed. Considering that a long delay time may slow down the process of construction, so it is necessary to choose a suitable delay time during the construction process.

The selection of each physical factor, which is included in the network input vector, is mainly based on the specifications of pile foundation construction and selection suggestion form hydraulic pile hammer designer. The vector of measurable pile machine physical parameters (p_a) is mainly used to distinguish different electro mechanical systems of hydraulic pile hammer. The parameters contained in vector p_a are the physical factors that have a significant impact on the simulation results in the simulation model and can be accurately obtained, including: pile hammer mass, hydraulic cylinder inner diameter and cylinder rod diameter, etc. The historical data of the construction process vector (r) mainly includes: the historical construction parameters and the its corresponding pile hammer movement period. In this model, we have $r=\{s_{k-1},s_{k-2},\cdots,s_{k-i},t_{k-1},t_{k-2},\cdots,t_{k-i}\}$ and $i\in[1,5]$.

The PISMN proposed in this paper consists of two sub-networks: feature extraction network (marked as $\beta(\cdot)$) and prediction network (marked as $\mu(\cdot)$).The feature extraction network can be regarded as the encoder of historical data of pile machine construction. The input parameters of the network are: the measurable physical parameter vector and the historical data vector which is record under the same physical parameter condition. The output vector of the neural network represents the system feature $\hat{p}_u$, which is used to extract unmeasurable physical parameters that contained in historical data and used to reduce the dimension of input vector of prediction network. The prediction network is used to predict the period movement cycle of pile hammer, and the predicted value is denoted by $\hat{t}$. The prediction network input includes: the vector of controlling parameter during construction process (s), the measurable physical parameters of pile hammer (p_a) and system feature ($\hat{p}_u$) extracted by extraction network $\beta(\cdot)$.

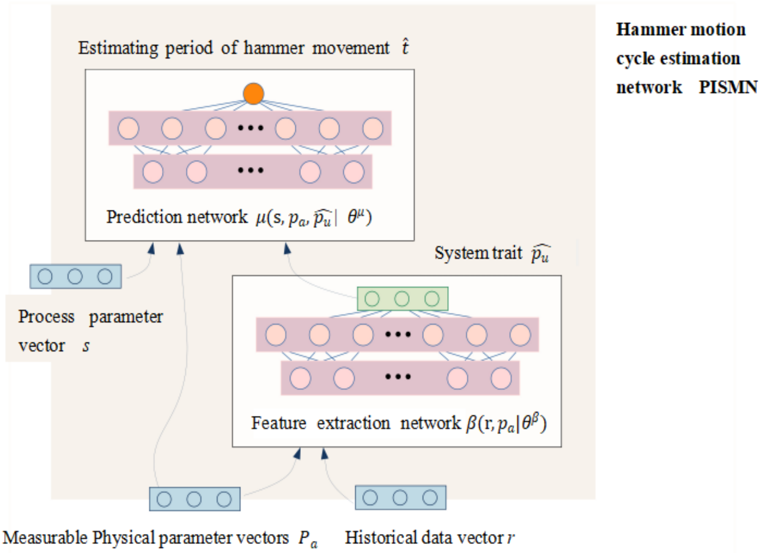

Figure 1: Structure of the PISMN algorithm

The number of hammer strikes per minute can be calculated directly through the reciprocating movement period of the pile hammer, which directly reflects the construction efficiency. In addition, the hydraulic efficiency of the pile hammer can be calculated by combining the pump outlet power and the lifting height of the pile hammer, which directly reflects the energy conversion efficiency of the pile hammer hydraulic system. The data transfer flow diagram of the surrogate model mentioned above is shown in the figure below (**Figure 2**).

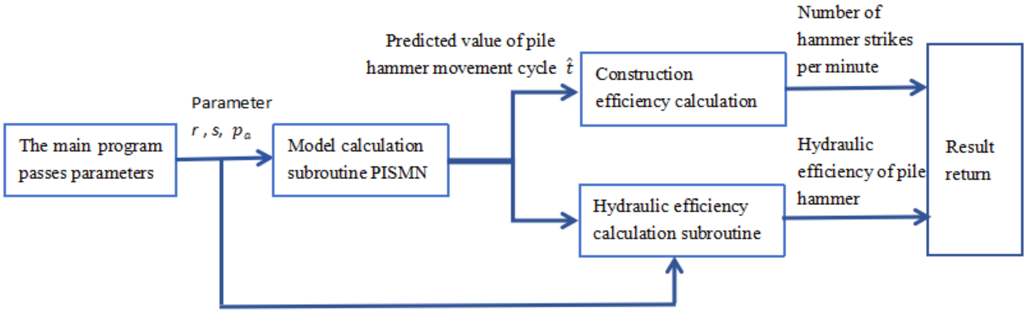

Figure 2: Flow chart of data in PISMN

2.2. Deployment of algorithms

The PISMN algorithm will fit the data set from the simulation platform mentioned in Chapter three. The simulation data generated in the platform include: the physical parameters $\{p_a, p_u\}$ of the hydraulic pile machine during simulation, where p_a are the parameters of the pile machine that can be measured , including the weight of the pile hammer (marked as m) ; the parameter p_u stands for pile machine parameters that are difficult to measure accurately , including overflow coefficient (marked as C_{im}, C_{em}), flow coefficient (marked as C_d) and so on. The above parameters are determined by the conclusion of Chapter two of this paper. Although the changes of these parameters have a great impact on the simulation results, the true values (marked as p_u) of these parameters will not be introduced into the PISMN training program. The PISMN network needs to extract the hidden features of physical parameter p_u which are contained in the historical data according to the historical parameters (marked as r) under the same physical parameters (marked as $\{p_a, p_u\}$) .

Table 1: The PISMN model training procedure pseudo-code

Algorithm 1 PISMN **Model training process**

Input : Simulation result data set R

Output : A trained predictive network model $\mu(\theta^{\mu})$;A trained feature extraction network model $\beta(\theta^{\beta})$; Optimization objective is:

$$\hat{\theta} = \arg\min \frac{1}{N}\sum_{i=1}^{N} L(t, \hat{t}, \gamma \mid \theta^{\mu}, \theta^{\beta})$$

1: function TRAIN-PISMN(R)

2: Initialize the simulation result R of the model analysis simulation platform, and establish the key-value pairs between parameter simulation parameter and simulation result.

3: while i < epoch do

4: Three groups of parameters { p_A, p_U, s } are randomly selected .

5: The construction parameters of the pile hammer and the corresponding movement period of the pile hammer under the other five groups of simulation parameters were randomly selected and recorded as r.

6: The predicted value of the movement period of the hammer is obtained by network forward calculation $\hat{t}$.

7: Obtain the partial derivative $\frac{\partial \hat{t}}{\partial h}$ of the network output with the drop weight height, and calculate the loss function L:

$$L = MSE(t, \hat{t}) + MSE_{penalty}(\gamma \cdot \max(-\frac{\partial \hat{t}}{\partial h}, 0), 0)$$

8: Update network model parameters:

$$\mu(\theta^{\mu}) \leftarrow \mu(\theta^{\mu(i+1)})$$

$$\beta(\theta^{\beta}) \leftarrow \beta(\theta^{\beta(i+1)})$$

9: end while

10: end function

The algorithm model training process is summarized as follows:

(1) The training process first loads the data set(R) of the simulation model, and establishes the

key-value pairs of the control parameters, physical parameters and the movement period of the pile hammer during the construction process of the pile machine, so as to realize the mapping between the input and output values during the training process. Then specify the training cycle, and enter the training cycle;

(2) Randomly select a set of physical parameters $\{p_a, p_u\}$; A set of construction parameters are selected based on the physical parameters, and the corresponding simulation software prediction results are recorded for the subsequent loss function calculation. Then, based on the physical parameters, another five groups of construction parameters and their corresponding pile hammer movement period are randomly selected as historical data (R).

(3) Parameters were passed into the PISMN feature extraction network to extract the features of the pile machine.

(4) Calculate the loss function, update the network parameters, and make it continuously optimized.

2.3. Experimental datasets

Based on the above, the training data set of the proxy model is generated by the simulation model. In the process of establishing the simulation platform, the degree of matching with the target model should be considered first. The high-fidelity digital model will improve the accuracy of the transfer learning algorithm in the process of predicting the data in the real machine domain. **Figure 3** shows the physical diagram and actual pile machine drawing of a certain type of hydraulic pile hammer.

Figure 3: Physical map and actual drawing of hydraulic pile hammer

For the hydraulic pile hammer simulation model, the relevant simulation test variables mainly focus on the physical quantities that have a certain impact on the hydraulic energy conversion rate of the model. The simulation database was established to record the following data contents: the values of all test factors in the simulation process, the simulation results (including the energy conversion efficiency of the hydraulic pile hammer in the process, the reciprocating movement cycle of the pile hammer, etc.). Among them, the test factor refers to a group of processed factors that are changed in the simulation process and are to be compared. Specific to this study are the physical quantities mentioned in before (overflow coefficient, flow coefficient, pile hammer mass, hydraulic cylinder internal geometry, etc.) and hydraulic pile hammer construction control parameters. Among them, the physical quantities that can be accurately measured will be read by the proposed algorithm in the subsequent research. The physical quantities that cannot be accurately measured are mainly used to record and distinguish different sets of simulation data. For the pneumatic test model, the simulation database is basically the same as that of the hydraulic pile hammer simulation model. Due to the characteristics of the pneumatic platform, the input power P of the hydraulic pump in the construction control parameters of the pile hammer in the platform is changed to the output pressure of the reducing valve.

Generally, the simulation process of simulation software is divided into:

(1) Build a simulation sketch according to the actual schematic diagram;

(2) Select the sub-model of each component according to the actual situation;

(3) Set relevant parameters of the model;

(4) Set test factors and design simulation batch process based on relevant test factors;

(5) Conduct the simulation process and record the relevant simulation results;

(6) Post-processing of simulation data to facilitate data input of PISMN model, which can also be called data preprocessing of PISMN model. The following figure (**Figure 4**) is the simulation flow chart.

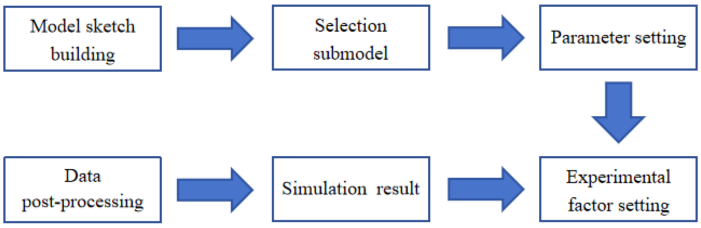

Figure 4: Simulation flow chart

3. EXPERIMENT AND RESULTS

In order to comprehensively evaluate the proposed agent model, this chapter will first introduce the training process of the neural network agent model, and then test the trained model with validation data set. In the above process, other neural network agent models will be used for horizontal comparative analysis. Finally, the influence of the physical knowledge embedding method on the agent model is further discussed.

3.1. Experimental results of model training

This section will first study the training process of the model, and compare the stability and convergence of different agent models in the training process. The following figure shows the change curves of the training process loss function of PISMN algorithm, BPNN algorithm and SGAN algorithm when the values are equal to 0, 0.5 and 1 respectively. At the same time, the variance of the return value of the training process loss function of each algorithm can be obtained through 10 repeated experiments. Then the curve and the area enclosed by it can be used to indicate that the return value of each method's loss function has a greater probability of falling in this region during the training process. When the parameter value of PISMN model described in the present paper is set to 0, the physical embedding method will no longer play an optimization role on the original network. Therefore, the following text will use the identification SMN to represent: the PISMN algorithm at that time. In addition, PISMN-G0.5 and PISMN-G1 methods shown in the figure respectively represent the PISMN algorithm when γ equals to 0.5 or 1.

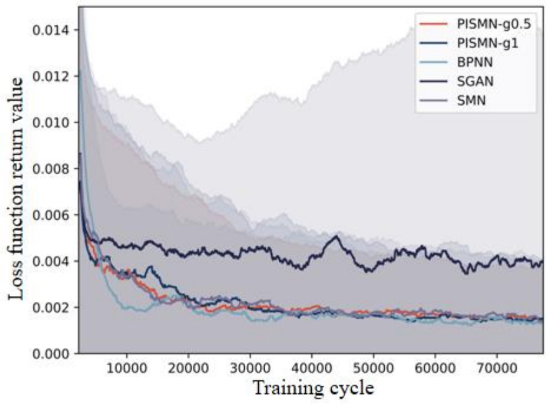

Figure 5: Change curve of loss function in training process of each algorithm

It can be observed from the experimental results in the following figure that all algorithms can converge effectively under this research background. However, the changes in the return value of the loss function of each algorithm are quite different. Among them, the convergence speed of the BPNN algorithm is faster, and the return value of the loss function at the end of training is also slightly lower than that of the PISMN algorithm. However, it can be seen from the research in the verification set in the following paper that the BPNN algorithm has overfitting phenomenon. Compared with other algorithms, there is a big difference between SGAN algorithm and other algorithms in the return value of loss function at the end of training process. In the relevant research of adversarial neural networks (Gans), problems such as non-convergence, mode collapse and slow convergence speed have become important constraints restricting the further application of GAN and its derivative methods. Although the SGAN algorithm is used to replace the traditional GAN algorithm, and the parameters of the SGAN algorithm are also optimized, the experimental results show that such a generation model is not suitable for the regression problem in the background of this study.

The following figures (**Figure 6** and **7**) shows the change curve of the ratio between the predicted value and the true value in the training process of each algorithm. In the figure, each algorithm uses two curves respectively to show this result. The two curves respectively represent the sum and difference of the mean and standard deviation of the ratio of predicted value and true value in 10 repeated experiments. The experimental results show that at the beginning of training, all the algorithms can quickly converge to within 10% error. However, at the end of the training stage, all the data within one standard deviation of the ratio of predicted value to true value fell within 5% deviation range in all samples of all algorithms except SGAN algorithm.

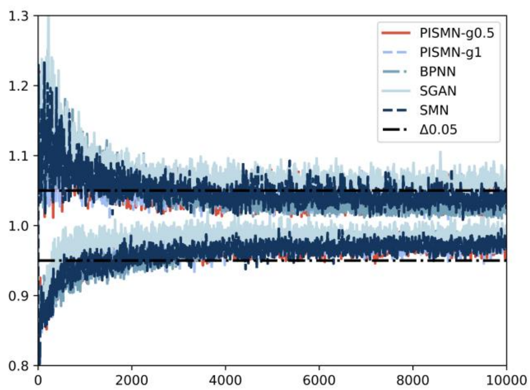

Figure 6: Local diagram at the beginning of training

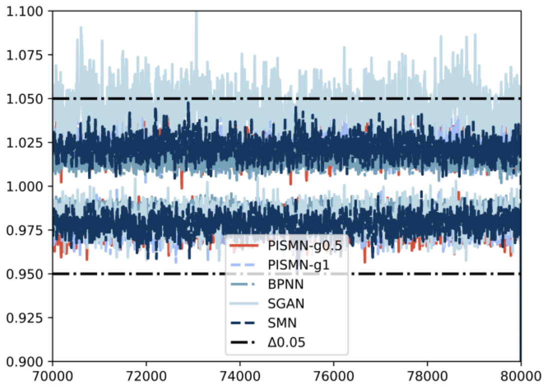

Figure 7: Local diagram at the end of training

3.2. Analysis of test set verification results

In order to evaluate each neural network agent model objectively, the following test sets are set to verify the comparison experiment. That is, after the training is completed, the data not used in the training process of the model (which does not affect the selection of ordinary parameters or hyperparameters) is used to perform an unbiased estimation of the prediction performance of the model.

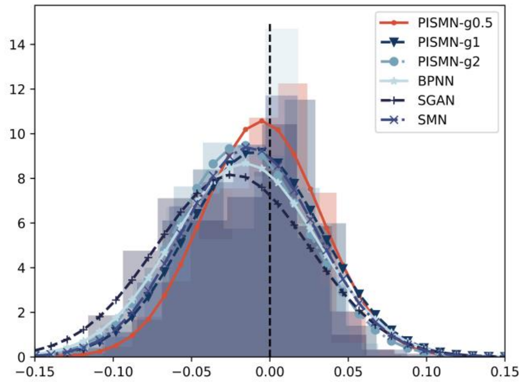

Figure 8: The absolute error distribution diagram of each algorithm in verification set 1

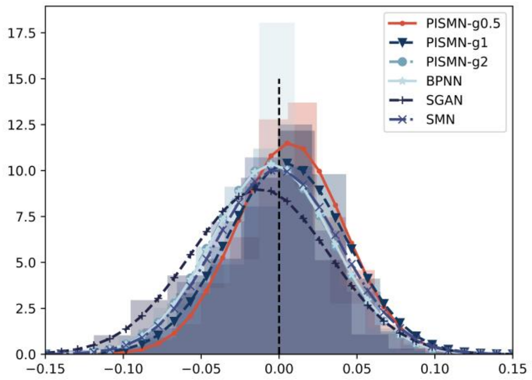

Figure 9: The absolute error distribution diagram of each algorithm in verification set 2

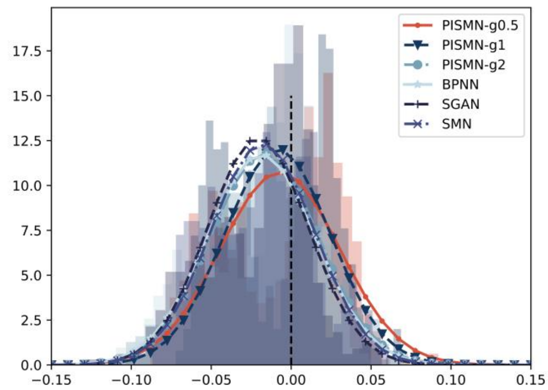

Figure 10: The absolute error distribution diagram of each algorithm in verification set 3

In the test experiments for each model, three validation sets with different uses were used. Each verification set is used separately to generate simulation parameters of the simulation model different from the training set. **Figure 8** to **Figure 10** respectively show the absolute error distribution diagram of the predicted values of each algorithm in the three verification sets.

According to the relevant data, in verification set 1, PISMN model with a value of 0.5 is superior to other methods in multiple indicators. In verification set 2, the BPNN method has a smaller deviation to the original simulation model, but the number of outliers is larger and the span of outliers is larger. In the relevant verification results of verification set 3, PISMN algorithm has better comprehensive performance, and the median and average of predicted value deviation have better performance in related algorithms. At the same time, it can be observed from Figure 3-18 that only two outliers appear in SGAN algorithm, and the variance of prediction bias of each algorithm has no significant change compared with the experimental results of other verification sets. The reason for this phenomenon may be that the degree of similarity between the data of verification set 3 and the training set is higher than that of verification set 1 and verification set 2. In addition, the prediction errors of each algorithm basically meet the normal distribution and meet the expectation. At the same time, it can be seen from Table 3-2 that when the value is 0.5, PISMN method can improve the prediction deviation median and mean accuracy by more than 54.4% compared with other algorithms in verification set I and verification Set III, and its comprehensive performance is significantly better than other comparison methods.

Further, from **Figure 8** to **Figure 10** above, it can be observed that the agent model optimized by the physical embedding method (i.e., the agent model with values of γ of 0.5 and 1 respectively) has a smaller difference between the upper and lower limits of the deviation of outliers, and the number of outliers distributed on both sides of the line γ=0 is more uniform than that of other agent models optimized by the physical embedding method. Therefore, it can be concluded that compared with the original model, the prediction accuracy and predicted value fluctuation of the model optimized by the physics knowledge embedding method are optimized to some extent. That is, by introducing the physical embedding method, the loss function term of the model is improved, which has a positive effect on the comprehensive performance of the agent model neural network.

From the above analysis, the conclusion of this section can be drawn: SGAN algorithm is not suitable for this research background, and BPNN method can converge faster than other algorithms. The PISMN method proposed in this paper and its derivative methods can converge stably. At the same time, the stable convergence of the algorithms also proves that it is feasible to explore the physical parameters of the pile machine by using the historical data (marked as r) of the hydraulic pile hammer. PISMN method has more stable performance and higher prediction accuracy than other algorithms in multiple verification sets. The comparison of SMN and PISMN ablation experiments also proved that the physics knowledge embedding method can improve the comprehensive performance of the model.

4. DISCUSSION AND CONCLUSION

In this chapter, the agent model based on neural network is constructed, and the agent model of digital simulation of hydraulic pile hammer is constructed while extracting the relevant information of pile hammer by using the historical operation data of pile machine. The proxy model consists of two parts: the feature extraction network of historical data and the cycle prediction network of hammer movement. Among them, the function of the feature extraction network is to extract the physical parameters of the pile machine contained in the historical data, and pass them into the predictive neural network together with the measurable physical parameters and the construction control parameters of the pile machine, and finally achieve the prediction of the movement cycle of the pile hammer. Among them, the effectiveness of feature extraction network will be further discussed in the next chapter. By comparing PISMN network with other neural network-based proxy model algorithms, it can be concluded that PISMN has certain advantages in convergence speed and prediction accuracy.

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