Prediction of Drag Coefficient for Non-Spherical Particles Based on Artificial Neural Network Models: Postprint

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Abstract

This study employs artificial neural network prediction methods to predict and analyze the gas-solid drag coefficient for non-spherical particles. Initially, a comparative analysis was conducted between the BP (Backpropagation) neural network model and the RBF (Radial Basis Function) neural network model in predicting results from the experimental conditions of Pettyjohn and Christiansen et al. The findings demonstrate that the RBF method achieves smaller errors and higher computational efficiency in predicting the gas-solid drag coefficient for non-spherical particles. Furthermore, the RBF neural network model was utilized to predict and analyze the gas-solid drag coefficient under different shape factors. The research results indicate that artificial neural networks can be applied to predictive studies of gas-solid drag coefficients for non-spherical particles, and the findings of this paper provide an effective methodology for predicting drag coefficients of particles with complex shapes.

Full Text

Preamble

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Prediction of Drag Coefficient for Non-spherical Particles Based on Artificial Neural Network Models

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Abstract

This paper presents the prediction and analysis of gas-solid drag coefficients for non-spherical particles using artificial neural network methods. The performance of BP (Backpropagation) neural network models and RBF (Radial Basis Function) neural network models is first compared in predicting experimental results from Pettyjohn and Christiansen et al. The results demonstrate that the RBF method yields smaller prediction errors and higher computational efficiency for non-spherical particle gas-solid drag coefficients. Furthermore, the RBF neural network model is applied to predict and analyze gas-solid drag coefficients under various shape factors. The findings indicate that artificial neural networks can be effectively used for predicting non-spherical particle gas-solid drag coefficients, providing a valuable approach for estimating drag coefficients in complex-shaped particle systems.

Keywords: artificial neural network; non-spherical particles; drag coefficient

0 Introduction

The transport of solid particles in continuous fluids is a ubiquitous phenomenon. Researchers have conducted extensive experimental and numerical investigations on particle transport processes [1-2]. However, most studies have focused on spherical particles, while non-spherical particles inevitably exist in actual industrial processes. Due to the presence of shape factors, non-spherical particles exhibit significantly different motion characteristics compared to spherical particles. Consequently, investigating the motion of non-spherical particles in continuous fluids is essential. During particle transport in fluids, momentum exchange between gas and solid phases plays a crucial role in controlling particle behavior. Researchers have developed drag models to describe this momentum exchange, where the selection and calculation of drag coefficients critically affect the accuracy of drag computations.

Experimental methods represent a relatively straightforward approach for studying drag coefficients of particles moving freely in fluids. Researchers have primarily employed settling tubes and wind tunnel experiments to predict drag coefficients for non-spherical particles [3-4]. Nevertheless, experimental measurement methods have limitations. For instance, wind tunnel methods require large experimental spaces, involve complex debugging and installation procedures, and demand substantial human and material resources.

In recent years, artificial neural network models have advanced considerably. Due to their ability to accurately estimate complex problems, higher efficiency compared to empirical models, and robustness to incomplete and noisy input data, artificial neural network models are being widely applied across various disciplines. These models can effectively compensate for the shortcomings of experimental methods. In fluidization research, neural network models have been successfully employed to predict and analyze NOx formation in fluidized beds, detect and predict leakage phenomena, and model solid waste gasification processes [5-6]. However, few studies have applied artificial neural network models to investigate gas-solid drag coefficients.

In summary, research on predicting gas-solid drag coefficients for non-spherical particles using neural network models remains scarce. Therefore, this study employs neural network models for this purpose. First, the prediction performance of BP and RBF neural network models is compared, and their prediction errors are discussed. Subsequently, the RBF model is used to predict and analyze gas-solid drag coefficients for non-spherical particles, providing the variation of drag coefficients with Reynolds number under different shape factors.

1 Artificial Neural Network Model

Artificial Neural Network (ANN), commonly referred to as neural network model, is a data processing model inspired by biological neural networks, designed to emulate the structure and information processing functions of the human brain. Neural network models are computational tools composed of numerous simple, highly interconnected neurons defined by researchers. Through dynamic system responses to external input signals, neural network methods can learn highly nonlinear relationships and process information [7-8].

In 1974, Werbos et al. [10] first proposed the BP algorithm for neural network learning, providing a practical solution for training and implementing multi-layer neural networks. In 1986, Rumelhart and McClelland [9] conducted a detailed analysis of the error backpropagation algorithm for multi-layer networks, solving the learning problem for multi-layer neural networks and further advancing the development of the BP algorithm. The topological structure of BP networks includes an input layer, hidden layer, and output layer, enabling them to store complex mapping relationships through learning without requiring explicit mathematical expressions between inputs and outputs. In BP networks, parameter learning typically employs the error backpropagation algorithm, where data propagates backward from the input layer through hidden layers, and network connection weights are corrected forward from the output layer through intermediate layers along the opposite direction of the error performance function gradient using the steepest descent method. The BP network model is illustrated in Figure 1 [Figure 1: see original paper].

While the BP algorithm partially solved the challenge of parameter training for multi-layer networks, it has inherent limitations. First, the BP algorithm requires numerous parameters, such as network layers, neuron counts per layer, and weight values, yet lacks effective methods for parameter selection. Second, the BP algorithm employs steepest gradient descent optimization, which frequently becomes trapped in local minima, leading to suboptimal solutions. Third, the BP algorithm is highly dependent on sample quality; poor sample representativeness, contradictory samples, or redundant samples degrade network performance. Finally, for complex network optimization problems, the BP algorithm' s learning rate constraints can require several hours of computation. Consequently, researchers have developed new neural network models to address these deficiencies.

1.2 RBF Neural Network Method

In 1988, based on the local response characteristics of biological neurons, Broomhead and Lowe introduced radial basis functions into neural network design [10], proposing the Radial Basis Function (RBF) neural network algorithm. Subsequently, Jackson and Park [11-12] demonstrated the uniform approximation capability of RBF algorithms for nonlinear continuous functions in 1989 and 1991, respectively. RBF neural networks are three-layer feedforward networks whose fundamental working principle involves projecting low-dimensional input vectors into a nonlinear hidden layer space constructed by RBFs, transforming data into a high-dimensional space to render originally linearly inseparable problems linearly separable, ultimately producing a linear output layer. Figure 2 [Figure 2: see original paper] shows the basic structure of the radial basis neural network.

RBF networks exhibit rapid learning convergence, primarily due to their simple structure and fast convergence speed, eliminating the need to learn hidden layer weights and avoiding the time-consuming process of error propagation through network layers. The research and application of RBF networks marked the practical advancement of neural networks and have been widely applied in nonlinear function approximation, pattern classification, control system modeling, time-varying data analysis, and fault diagnosis.

In this study, the input parameters are Reynolds number (Re) and shape factor (Φ), with the expected output being the gas-solid drag coefficient. Experimental values from existing literature are used as training data to predict the variation of gas-solid drag coefficients with Reynolds number under different shape factors.

2 Results and Discussion

2.1 Comparison of BP and RBF Algorithm Results

This section first compares the prediction results of BP and RBF methods for drag coefficients with different shape factors from literature. Experiments by Pettyjohn and Christiansen et al. [13] provided experimental drag coefficient distributions for shape factors of 0.670, 0.806, 0.846, 0.906, and 1.000. This study uses experimental results for shape factors of 0.670, 0.846, and 1.000 for training and learning, then predicts drag coefficient distributions for all five shape factors and compares them with experimental results, as shown in Figure 3 [Figure 3: see original paper].

For a shape factor of 0.906, both BP and RBF methods produce drag coefficient predictions relatively close to experimental values, but the BP method requires significantly longer computation time than the RBF method, as shown in Table 1 . For a shape factor of 0.806, the RBF method predictions show better agreement with experimental results, as illustrated in Figure 3(b).

Table 1 compares the computation times for predicting drag coefficients under different shape factors using BP and RBF methods. The results clearly show that under the same operating environment, the BP method requires approximately 80 seconds on average, while the RBF method requires only about 8 seconds—merely 10% of the BP method's time. This demonstrates that the RBF method offers significantly higher computational efficiency when using identical datasets for learning and training to predict drag coefficients for the same shape factor.

Figure 4 [Figure 4: see original paper] presents the average error distributions between predicted and experimental results for particles with different shape factors. The RBF method consistently maintains prediction errors below 10% with stable error distribution. In contrast, the BP method exhibits large fluctuations in prediction errors, particularly for a shape factor of 0.670, where the error approaches 21%, with overall error distribution ranging between 10% and 20%, indicating poor reliability.

In summary, the RBF method produces predictions closer to experimental values with smaller errors and higher efficiency, representing a more reasonable and effective approach for predicting gas-solid drag coefficients of particles with various shape factors. This method provides a more rational theoretical basis for drag coefficient selection under different shape factor conditions. Therefore, this study employs the RBF method for subsequent prediction and analysis of gas-solid drag coefficients for non-spherical particles with different shape factors.

2.2 Prediction of Drag Coefficients for Different Shape Factors

As demonstrated above, the RBF method can effectively predict gas-solid drag coefficients under various shape factor conditions with relatively short computation time. Pettyjohn and Christiansen et al. [13] provided five sets of experimental data, of which three sets were selected for training in this study. The trained model was used to predict drag coefficients for the training data shape factors and compared with experimental results, as shown in Figure 5 [Figure 5: see original paper].

To further validate the RBF prediction method, the trained model was applied to predict drag coefficients for the remaining two shape factor cases and compared with experimental results, as shown in Figure 6 [Figure 6: see original paper]. The predictions show good agreement with experimental data. At the Reynolds number transition point (Re=100), slight deviations occur between predictions and experiments, but the overall prediction accuracy remains close to experimental results with average errors of approximately 7% and 8%.

Figure 7 [Figure 7: see original paper] presents the predicted gas-solid drag coefficients for different shape factor particles using the RBF model. The study predicts drag coefficient distributions for shape factors of 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0. The results reveal similar variation patterns across different shape factors: for $Re<10$, drag coefficients vary nearly linearly with Reynolds number, decreasing as Re increases; for $10<Re<100$, the variation trend gradually flattens; for $Re>100$, drag coefficients remain essentially constant. Comparison across shape factors shows that drag coefficients are relatively close to each other when Re<1. However, when Re>1, differences become increasingly pronounced, and the influence of shape factor on drag coefficient strengthens with increasing Reynolds number. For Re>100, drag coefficients for different shape factors show slight increases but remain essentially unchanged.

In conclusion, the neural network approach can effectively predict gas-solid drag coefficients under various shape factors. The results demonstrate that shape factor effects on drag coefficient cannot be neglected, and this work provides valuable reference for predicting and constructing gas-solid drag models for non-spherical particles.

3 Conclusions

This study employs artificial neural network models to predict and analyze gas-solid drag coefficients for non-spherical particles, comparing simulation results with experimental data from literature. The findings demonstrate that artificial neural networks can be applied to predict gas-solid drag coefficients for non-spherical particles. The main conclusions are:

(1) Comparison of BP and RBF model predictions with experimental results reveals that the RBF model produces predictions closer to experimental values with smaller errors and higher computational efficiency.

(2) Using the RBF method to predict drag coefficient distributions under different shape factors shows that the variation trends of drag coefficient with Reynolds number are fundamentally similar across shape factors.

(3) At the same Reynolds number, drag coefficients increase as shape factors decrease.

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Note: Figure translations are in progress. See original paper for figures.