Drag Coefficient Prediction for Non-Spherical Particles Based on Artificial Neural Network Models: A 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, the BP (Backpropagation) neural network model and the RBF (Radial Basis Function) neural network model were compared in their predictions of results from the experimental conditions of Pettyjohn and Christiansen et al. The findings indicate that the RBF method achieves smaller prediction errors and higher computational efficiency for the gas-solid drag coefficient of non-spherical particles. Furthermore, the RBF neural network model was applied to predict and analyze the gas-solid drag coefficient under various shape factors. The research results demonstrate that artificial neural networks can be utilized for predicting the gas-solid drag coefficient of non-spherical particles, and the present study provides an effective methodology for predicting the gas-solid drag coefficient of complex-shaped particles.

Full Text

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

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Abstract

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

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

0 Introduction

The transport of solid particles in continuous fluids represents a ubiquitous phenomenon that has been extensively investigated through both experimental and numerical approaches. However, most studies have focused on spherical particles, whereas non-spherical particles inevitably exist in practical industrial processes. Due to the influence of shape factors, the transport characteristics of non-spherical particles differ significantly from those of spherical particles. Consequently, investigating the motion of non-spherical particles in continuous fluids is essential. In particle-fluid transport processes, momentum exchange between gas and solid phases plays a crucial role in controlling particle behavior. Researchers describe this momentum exchange through drag models, where the selection and calculation of drag coefficients critically affect the accuracy of drag computations.

Experimental methods, such as settling tube and wind tunnel experiments, have been commonly employed to determine drag coefficients for non-spherical particles. Nevertheless, experimental approaches suffer from limitations including large spatial requirements, complex installation and debugging procedures, and substantial consumption of human and material resources. In recent years, artificial neural network models have achieved considerable development and offer several advantages: they can accurately estimate complex problems, operate more efficiently than empirical models, and handle incomplete or noisy input data more effectively. As a result, neural network models are increasingly applied across various disciplines, effectively overcoming the shortcomings of experimental methods. In the field of fluidization, neural network models have been successfully used to predict and analyze NOx generation, leak detection, and solid waste gasification in fluidized beds, yielding promising results. However, the application of artificial neural network models to investigate gas-solid drag coefficients remains scarce.

This study addresses this research gap by employing neural network models to predict the gas-solid drag coefficient for non-spherical particles. The prediction performance of BP and RBF neural network models is first compared and discussed. Subsequently, the RBF model is utilized to predict and analyze the drag coefficient for non-spherical particles, examining its variation with Reynolds number under different shape factors.

1 Artificial Neural Network Model

An Artificial Neural Network (ANN), commonly referred to as a neural network model, is a data processing framework inspired by biological neural networks. It aims to emulate the information processing system of the human brain. Neural networks consist of numerous simple, highly interconnected neurons defined by researchers, enabling them to learn highly nonlinear relationships and process information through dynamic system responses to external input signals.

In 1974, Werbos et al. 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 et al. conducted a detailed analysis of the error backpropagation algorithm for multi-layer networks, addressing learning challenges in multi-layer neural networks and advancing the development of the BP algorithm. The topological structure of BP networks comprises an input layer, hidden layer(s), and output layer, capable of storing complex mapping relationships through learning without requiring explicit mathematical expressions. In BP networks, parameter learning typically employs the error backpropagation algorithm, where data flows forward from the input layer through hidden layers, while connection weights are adjusted 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 architecture is illustrated in [Figure 1: see original paper].

Despite solving training difficulties for multi-layer networks, the BP algorithm has several limitations. First, it requires numerous parameters such as network layers, neuron counts per layer, and weight values, yet lacks effective methods for parameter selection. Second, its optimization based on steepest gradient descent often leads to local minima, causing the algorithm to become trapped in suboptimal solutions. Third, BP algorithms are highly dependent on sample quality; poor representativeness, contradictory samples, or redundant data significantly degrade network performance. Finally, for complex optimization problems, BP algorithms may require hours due to learning rate constraints. These limitations have motivated researchers to develop new neural network models.

In 1988, Broomhead and Lowe introduced radial basis functions into neural network design based on the local response characteristics of biological neurons, proposing the Radial Basis Function (RBF) neural network algorithm. Subsequently, Jackson and Park 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 that project low-dimensional input vectors into a high-dimensional nonlinear hidden layer space, transforming linearly inseparable problems into linearly separable ones to obtain a linear output layer. The basic structure of an RBF neural network is shown in [Figure 2: see original paper].

RBF networks exhibit rapid learning convergence due to their simple architecture, fast convergence speed, and absence of hidden layer weight learning processes, eliminating time-consuming error backpropagation. The development and application of RBF networks marked the practical advancement of neural networks, with current applications spanning 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 data from existing literature serve as training data to predict the variation of gas-solid drag coefficient with Reynolds number under different shape factors.

2.1 Comparison of BP and RBF Algorithm Results

This section compares the prediction results of BP and RBF methods for drag coefficients with different shape factors reported in literature. Experiments by Pettyjohn and Christiansen et al. provided 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, then predicts drag coefficient distributions for all five shape factors and compares them with experimental data. The comparison results are presented in [Figure 3: see original paper].

For a shape factor of 0.906, both BP and RBF methods yield predictions close to experimental results, though BP requires significantly longer computation time than RBF, as shown in . For a shape factor of 0.806, the RBF method demonstrates better agreement with experimental results [FIGURE:3(b)].

The computation time comparison between BP and RBF methods for different shape factors is summarized in . Under identical operating conditions, BP method computation times average approximately 80 seconds, whereas RBF method computation times are around 8 seconds—only 10% of the BP method duration. This demonstrates that RBF offers substantially higher computational efficiency when using equivalent training data to predict drag coefficients for the same shape factors.

[Figure 4: see original paper] illustrates the average error distributions between predicted and experimental results for different shape factors. The RBF method maintains prediction errors consistently below 10% with stable error distribution. In contrast, BP method errors fluctuate considerably, reaching nearly 21% for a shape factor of 0.670, with error distributions ranging between 10% and 20%, indicating lower 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. Consequently, this study employs the RBF method for subsequent prediction and analysis of drag coefficients under different shape factor conditions.

2.2 Drag Coefficient Prediction for Different Shape Factors

Based on the above comparison, the RBF method effectively predicts gas-solid drag coefficients for various shape factors with minimal computational cost. The experimental results of Pettyjohn and Christiansen et al. provide five datasets; this study selects three for training and predicts drag coefficients for both training and prediction cases. The comparison with experimental results is shown in [Figure 5: see original paper]. For a shape factor of 1.0, the prediction agrees well with experimental data, confirming that predictions on training data yield satisfactory results.

The drag coefficient decreases gradually with increasing Reynolds number, remaining essentially constant when Re approaches 100, but showing a slight increase at Re = 1000. The average prediction error compared with experimental results is 8%. To further validate the RBF prediction method, the trained model was applied to predict the remaining two shape factor cases, with comparisons shown in [Figure 6: see original paper]. The predictions agree well with experimental data, showing only slight deviations at the Reynolds number transition point (Re = 100). The average prediction errors are approximately 7% and 8%, demonstrating that RBF predictions are sufficiently accurate to provide reasonable theoretical guidance for drag coefficient calculation of non-spherical particles.

[Figure 7: see original paper] presents RBF model predictions for gas-solid drag coefficients across different shape factors (0.5, 0.6, 0.7, 0.8, 0.9, and 1.0). The variation of drag coefficient with Reynolds number follows similar trends across all shape factors: for $Re < 10$, drag coefficient varies nearly linearly with Reynolds number, decreasing as Re increases; for $10 < Re < 100$, the variation trend gradually stabilizes; for $Re > 100$, the drag coefficient remains essentially constant. Comparison across shape factors reveals that drag coefficients are relatively similar at $Re < 1$, but differences become increasingly pronounced at $Re > 1$, with shape factor effects strengthening as Reynolds number increases. At $Re > 100$, drag coefficients for different shape factors show slight numerical increases with Reynolds number while remaining essentially stable.

3 Conclusions

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

(1) Comparison between BP and RBF model predictions reveals that the RBF model yields results closer to experimental data with smaller errors and higher computational efficiency.

(2) RBF method predictions of drag coefficient distributions under various shape factors show that the variation trends with Reynolds number are fundamentally similar across different shape factors.

(3) At constant Reynolds number, the drag coefficient increases as the shape factor decreases.

In summary, the neural network approach effectively predicts gas-solid drag coefficients across different shape factors. The results indicate that shape factor effects on drag coefficient cannot be neglected. This work provides valuable reference for the prediction and modeling of gas-solid drag coefficients for non-spherical particles.

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