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Prediction of Nusselt number of heated cylinder exposed to turbulent flow by deep long short-term memory network optimized by particle swarm algorithm

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ABSTRACT: Leveraging artificial intelligence to forecast heat transfer characteristics across diverse industries holds significant potential for improving thermal equipment design, increasing heat transfer efficiency, optimizing cooling systems, and reducing energy consumption. The main contribution and purpose of the current study is predicting the Nusselt number in the context of turbulent flow-induced vibration around a heated cylinder experiencing unconfined oscillations along both streamwise and transverse axes. The anticipation of the Nusselt number relies on transverse and streamwise displacements of the oscillating cylinder and encompasses three distinct scenarios: displacement input in the x-direction, displacement input in the y-direction, and comprehensive amalgamation of both x and y inputs. This prediction is achieved through a sophisticated deep long short-term memory network, meticulously crafted and fine-tuned using a particle swarm optimization algorithm. The results highlight the effectiveness of the optimized networks across various inputs, with the highest predictive precision observed when employing combined x and y inputs. The correlation coefficients within the test segment are as follows: 0.967 for x input, 0.961 for y input, and 0.975 for combined x and y inputs. By applying the methodology elucidated in this study, the forecasting of heat transfer characteristics for structures subjected to fluid flow emerges as a feasible possibility.

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1- Introduction

The study of heat transfer in the field of vortex-induced vibration (VIV) encompasses various engineering and research areas, including computational fluid dynamics, structural mechanics, and thermal sciences. When a heated cylinder is immersed in fluid flow, complex interactions arise between the convective heat transfer from the fluid and the dynamic response of the cylinder due to fluid-induced vibrations. Understanding these interactions is crucial for numerous engineering applications, such as designing heat exchangers and offshore structures [1]. Predicting the Nusselt number in the context of vortex-induced vibration is vital because of its significant role in a wide range of engineering applications [2, 3]. Accurate predictions of the Nusselt number can enhance the efficiency and safety of various industrial systems. Recently, the application of machine learning methods in heat transfer science has expanded, yielding significant results. For example, Zhai et al. [4] used random forest machine learning algorithms to improve experimental correlations for microchannel membrane-based adsorbents. Sundar et al. [5] experimentally estimated the thermal efficiency, heat transfer coefficient, and friction coefficient in a solar collector using MgO/water nanofluid. Han et al. [6] investigated the heat transfer and complex flow behaviors in a supercritical CO2 Brayton cycle precooler. Vu et al. [7] developed a machine-learning model to accurately predict the heat transfer coefficient between glass and steel surfaces.

A review of the literature reveals several studies on (1) vortex-induced vibration of oscillating structures, (2) heat transfer characteristics of heated vibrating cylinders, and (3) the application of various machine learning methods, particularly artificial neural networks, in thermal sciences. However, there has not been a comprehensive study focusing on the prediction of heat transfer characteristics in the context of flow-induced vibration, specifically with temporal behavior in mind. The main novelty and contribution of this work lie in employing a new method for predicting time series: the long-short-term memory network (LSTM) optimized by the particle swarm optimization algorithm (PSO). This method is used to predict the temporal behavior of the Nusselt number for a heated cylinder placed on an elastic bed in a turbulent flow.

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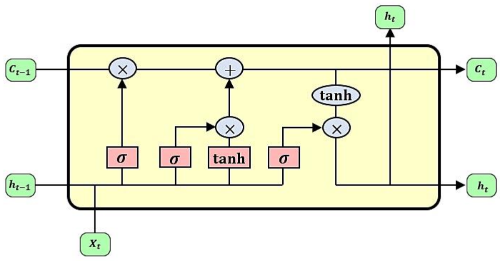

Fig. 1. A neural unit of the long short-term memory network

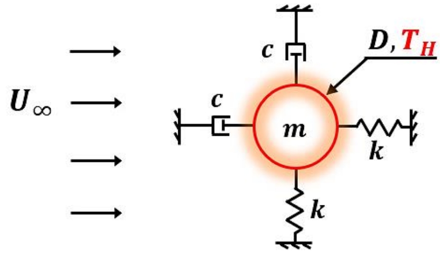

Fig. 2. Schematic of the elastically-mounted heated cylinder

2- Methodology

Recurrent neural networks (RNNs) often face an overfitting problem, where the network either loses important information over time or accumulates too much data in its hidden state, negatively impacting the output. To address this issue, more advanced architectures like long short-term memory (LSTM) networks have been developed. LSTM networks use special structures to control the flow of information, allowing them to overcome the limitations of traditional RNNs, especially over longer periods. Figure 1 shows an LSTM unit.

Figure 2 illustrates a cylinder on an elastic bed at a constant temperature, exposed to a flow that causes it to oscillate freely in both transverse and longitudinal directions due to vortex shedding. In this study, the cylinders are assumed to be very long, and the vortex-induced vibration is modeled in two dimensions. The Reynolds number of the flow varies between 1700 and 13000 as the free flow speed increases. To model the turbulent flow, the unsteady Reynolds-Navier-Stokes intermediate approach is used. A well-known method for mathematically modeling VIV is the simple and classic mass-spring-damper model. Detailed descriptions of the numerical solution methods for turbulent flow and heat transfer, structural equations, computing network setup, boundary condition definitions, two-way flow-structure interaction, grid independence investigation, and validation of the numerical solution can be found in references [8].

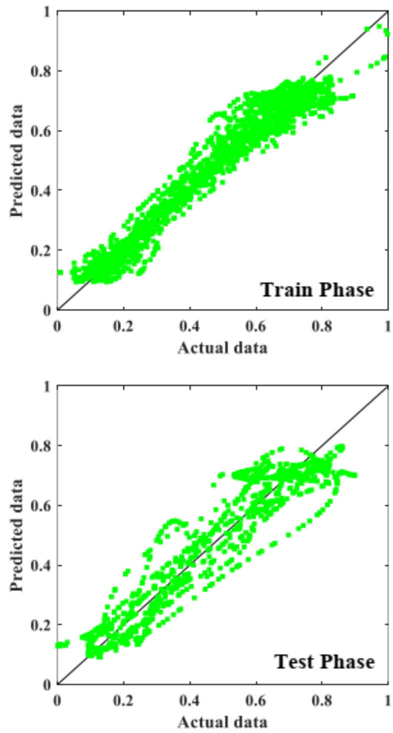

Fig. 3. Scatter plot for the network with input (x, y) for two phases of training and testing

3- Discussion and Results

The optimal parameters for the LSTM network were determined to be 4 hidden layers, 23 neurons, and a dropout rate of 0.138. The time response of the cylinder's displacements, and consequently the Nusselt number, is sinusoidal due to the fluctuating vortices and the oscillating lift and drag forces acting on the cylinder. Figure 3 presents the scatter diagram for the model with two inputs, x and y. The data correlation in the model with two inputs is higher than in the model with a single input. This increased correlation is evident in both the training and testing datasets. Figure 4 illustrates the temporal changes of the Nusselt number during the training and testing phases. It is clear that the machine learning model successfully predicted the Nusselt number. Additionally, the graph shows that the network's accuracy is higher during the training phase compared to the testing phase.

4- Conclusions

The key findings from this research are as follows: The cylinder's longitudinal vibration frequency is twice that of its transverse vibration frequency. Data correlation is better during the training phase than the testing phase because the network builds the model using the training data and has not encountered the testing data. The results indicate

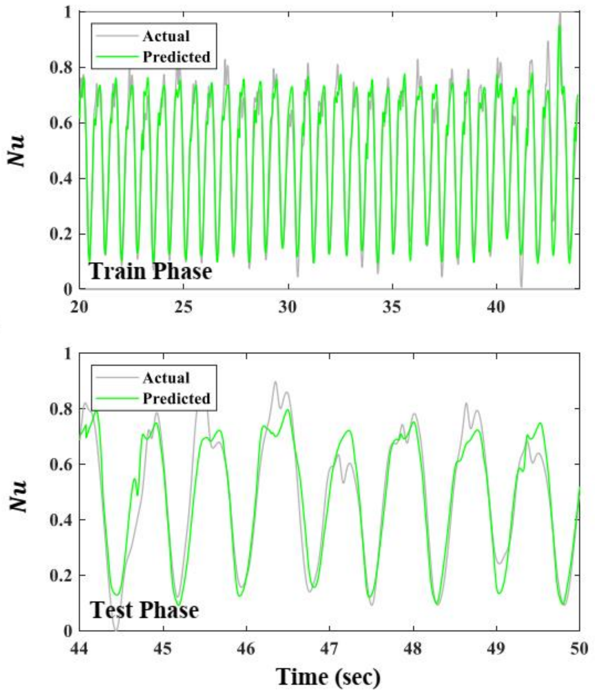

Fig. 4. Variation of the Nusselt number for the network with input (x, y) for two phases of training and testing

that predicting the Nusselt number based on the cylinder's transverse and longitudinal displacements is successful. This method could replace the complex and expensive techniques currently used for measuring the Nusselt number in various industries. Measuring the cylinder's displacement is straightforward with displacement sensors, and machine learning methods can be used to predict the heat transfer characteristics of structures based on this data.

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