An AI-Driven Pulsation Method of pVADs for Cardiac Digital Twins

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Abstract.
Research background and purpose: Currently, most percutaneous ventricular assist devices (pVADs) use a constant flow infusion method. Long-term use of a constant flow infusion device may increase the risk of adverse outcomes. Investigating pulsation methods for pVADs have significant importance for the development of cardiac digital twins.
Methods: A hydraulic experimental platform was established to capture the physical characteristics of pVADs across multidimensional operating conditions. Based on the experimental data, we propose a novel NPQ model defining the mathematical relationship among motor speed, pressure, and flow rate, alongside an LSTM-Transformer model to accurately predict pulsation characteristic time points.
Results: Experimental pressure-flow curves successfully determined the NPQ model parameters, which achieved a maximum pressure prediction error of only 2.15 mmHg. Furthermore, the LSTM-Transformer model demonstrated substantially lower prediction errors than conventional methods and maintained robust predictive performance across varying noise levels.
Conclusions: This study elucidates that pVAD motor speed exhibits a linear relationship with pressure and a quadratic relationship with flow rate. Both proposed models facilitate accurate predictions of pVAD pulsatile characteristics. Validated by extensive hydrodynamic experiments, they provide a solid foundation for realizing pVAD pulsatile function and developing cardiac digital twins.

Keywords: pVADs, pulsation method, hydraulic experimental platform, NPQ Model, LSTM-Transformer Model.

1 Introduction

For high-risk percutaneous coronary intervention (PCI) and cardiogenic shock(CS) patients[1], a percutaneous ventricular assist device (pVAD), also referred to as a blood pump[2], is one of the most effective mechanical circulation support devices(MCS)[3]. The pVADs can be classified based on their mode of assistance into the pulsatile and the continuous flow types[4, 5]. The pulsatile mode can provide perfusion that mimics the pulsating pressure and flow rate variations of the human heart[6]. The continuous flow mode, on the other hand, provides a constant pressure and flow rate. At present, the majority of pVADs are of the continuous flow type[4, 7]. However, prolonged use of continuous flow pVADs may lead to adverse symptoms such as gastrointestinal bleeding, pulmonary hypertension, and ventricular suction[8]. Therefore, pulsatile methods in pVADs can enable the generation of pulsatile flow that meets clinical requirements in both temporal synchronization and hemodynamic accuracy, which has fundamental importance for the future realization of cardiac digital twins[9, 10].

Two critical challenges remain in achieving pulsatile function for pVADs: (1) Hemodynamic accuracy, specifically involving the modulation of motor speed to deliver the precise pressure and flow values required by the patient[11]; therefore, establishing the mathematical relationships between motor speed, pressure, and flow rate is essential to ensure the device meets clinical hemodynamic requirements[3]. (2) Temporal synchronization, which entails identifying the pulsation characteristic time points for motor speed adjustment to synchronize pVAD-induced pulsatile flow with the patients' native cardiac flow[4, 12]. During operation, these characteristic time points must be predicted in advance, because: (1) the transmission, processing, and response of signals between the motor and sensors introduce inherent delays, meaning that real-time observation of blood pressure and flow in clinical surgery is insufficient for timely motor speed adjustment[4, 13]; (2) each patient possesses a unique heart rate, causing the pulsation characteristic time points to vary significantly between individuals[14]; (3) patients' characteristic time points may shift abruptly due to unexpected intraoperative events[15]. Consequently, providing pulsatile blood flow based on fixed time intervals is unfeasible, necessitating a time-series prediction model to forecast these time points for subsequent cardiac cycles.

Previous studies in the field of pVADs have elucidated the pairwise relationships between physical variables such as motor speed and pressure, as well as motor speed and flow rate[3]. However, the tripartite mathematical relationship among motor speed, pressure, and flow rate has yet to be explicitly defined. Additionally, although existing research has employed deep learning-based methods, such as LSTM, to predict the pulsation characteristic time points of pVADs[4, 16], these approaches are still characterized by significant prediction errors.

In this work, a hydraulic experimental platform for pVADs is first constructed to conduct comprehensive hydraulic experiments under multiple operating conditions (variable motor speeds) and across multiple dimensions. Based on these experiments, the pressure-flow (P-Q) curves of the pVAD are plotted, reflecting its fundamental physical characteristics. More importantly, two core models are developed: (1)The

NPQ Model: This model describes the mathematical relationship between motor speed, pressure and flow rate of the pVAD. Designed to ensure the hemodynamic accuracy of pressure and flow values provided by the pVAD, this model innovatively reveals the tripartite mathematical relationship between motor speed, pressure, and flow within the pVAD research field. (2)The LSTM-Transformer Model: This model is used to predict the pulsation characteristic time points of the patients' native blood pressure, aiming to achieve temporal synchronization between pVAD-supplied flow and native blood flow. The innovation of this model lies in the integration of the Attention module from the Transformer network with LSTM. By assigning importance weights to past input time series, the Attention module effectively addresses the "Long term dependency" problem[17] inherent in traditional time-series methods such as LSTM and GRU at the structural level of the neural network architecture[18]. Finally, multiple hydraulic experiments are conducted to validate the effectiveness of the NPQ Model and LSTM-Transformer Model, demonstrating their performance improvements over traditional methods.

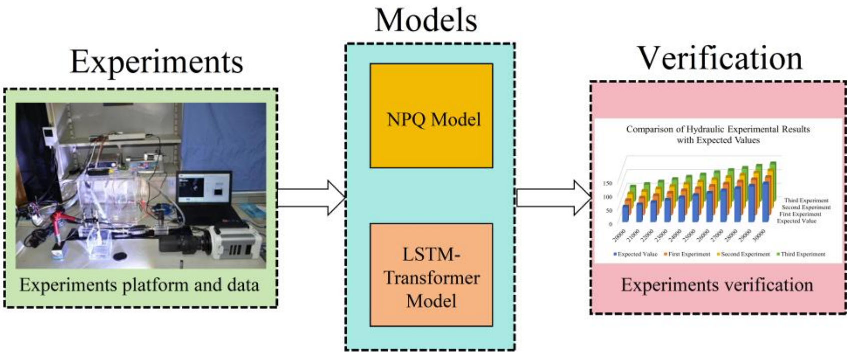

Fig. 1. Framework of this study

2 Methods

2.1 The construction of the pVAD hydraulic experimental platform

A pVAD hydraulic experimental platform is constructed, as illustrated in Fig. 2:

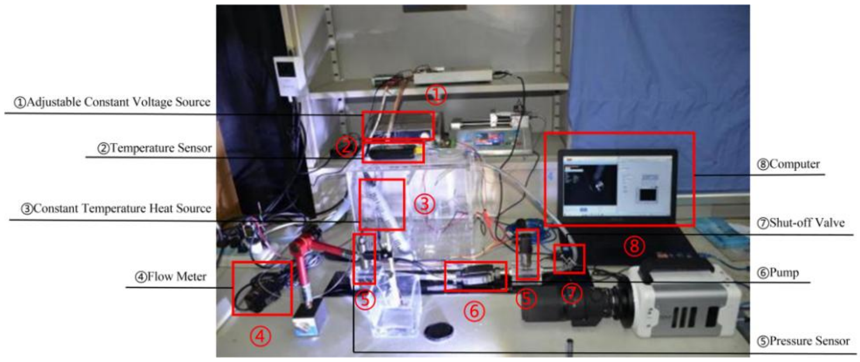

Fig. 2. Hydraulic Experimental Platform for the pVAD

Logic of the construction of the pVAD hydraulic experimental platform: Since this study focuses on the hemodynamics of pVADs during operation, the aim of the platform is to accurately measure physical quantities related to pVADs from a mechanical perspective. The tank simulates the environment within the human body. The left section of the tank simulates the human left ventricle, while the right section simulates the human aorta. The pVAD pumps the solution from the left section of the tank to the right section.The solution used in the hydraulic experiment consists of deionized water, alcohol, and glycerol in a ratio of 1:1:1 to simulate human blood. During this process, various physical quantities are measured.

2.2 Establishment of the NPQ Model

To investigate the mathematical relationships among the motor speed, pressure, and flow of the pVAD, a mathematical model for motor speed, pressure, and flow (NPQ Model) is proposed.

Bernoulli's equations are written for the pump inlet and outlet[19] as follows:

$$\begin{cases} \dfrac{p_1}{\rho} + \dfrac{v_1^2}{2} = C_1 \\ \dfrac{p_2}{\rho} + \dfrac{v_2^2}{2} = C_2 \end{cases} \tag{1}$$

where ρ represents the density of human blood, p_1 represents the pressure of the blood at the pump inlet, p_2 represents the pressure of the blood at the pump outlet, v_1 represents the flow velocity of the blood at the pump inlet, v_2 represents the flow velocity of the blood at the pump outlet, C_1 and C_2 are constants.

By organizing Equation(1), the following can be derived:

$$\frac{\Delta P}{\rho} + \frac{1}{2}\Delta(v^2) = \frac{N \cdot T \cdot (t_2 - t_1)}{\rho \cdot S \cdot \int_{t_1}^{t_2} v(t)dt} \tag{2}$$

where N represents the motor speed of the blood pump. P represents the pressure of the blood pump. T represents the pump motor torque. t_1 represents the time point for the blood to flow through the inlet. t_2 represents the time point for the blood to flow through the outlet. S represents the cross-sectional area of the blood flow within the pump. ΔP represents the pressure difference across the pump. $\Delta(v^2)$ represents the difference in the squares of the fluid velocities at both ends of the pump.

$$N = \frac{\Delta P \cdot Q}{T} + \frac{\Delta(v^2) \cdot \rho \cdot Q}{2T} \tag{3}$$

According to experimental results of pVADs, the torque T exhibits an approximately linear relationship with the flow rate Q. For a fixed pump cross-sectional area, $\Delta(v^2)$ varies linearly with the square of flow rate Q. Therefore, we derive that the motor rotational speed is approximately linearly proportional to pressure and proportional to the square of flow rate. To account for error terms including pump efficiency and viscous losses, correction factors a, b, and c are introduced into the formulation. The expression of the NPQ model is as follows:

$$N = a \cdot P + b \cdot Q^2 + c \tag{4}$$

In conclusion, the mathematical model for the motor speed, pressure, and flow rate of the pVAD is derived. Motor speed exhibits a linear relationship with pressure and a quadratic relationship with flow rate. By substituting the hydraulic experimental data of the pVAD into this model, undetermined coefficients a and b can be determined.

2.3 Establishment of the LSTM-Transformer Model

To study the pulsatile performance of the pVAD, an LSTM Transformer model is constructed to predict the pulsation characteristic time points. These points are defined as the specific time points at which the aortic pressure (AOP) signals of the patient begin to rise in each cardiac cycle[4]. In this study, the data for the pulsation characteristic time points are obtained by collecting simulated AOP signals that simulated by the pVAD hydraulic experimental platform. To address the "Long term dependency" problem[17] inherent in traditional methods[18] such as LSTM and GRU in pVAD research, this study innovatively combines the Attention module from the Transformer network with LSTM. This integrated approach is applied to the prediction of pulsation characteristic time points to improve accuracy and performance. The dataset contains 10871 samples and is split into the training set and test set at a 9:1 ratio. The model hyperparameters are set as follows: LSTM units = 8, attention heads = 4, dropout = 0.01, batch size = 64, epochs = 100.

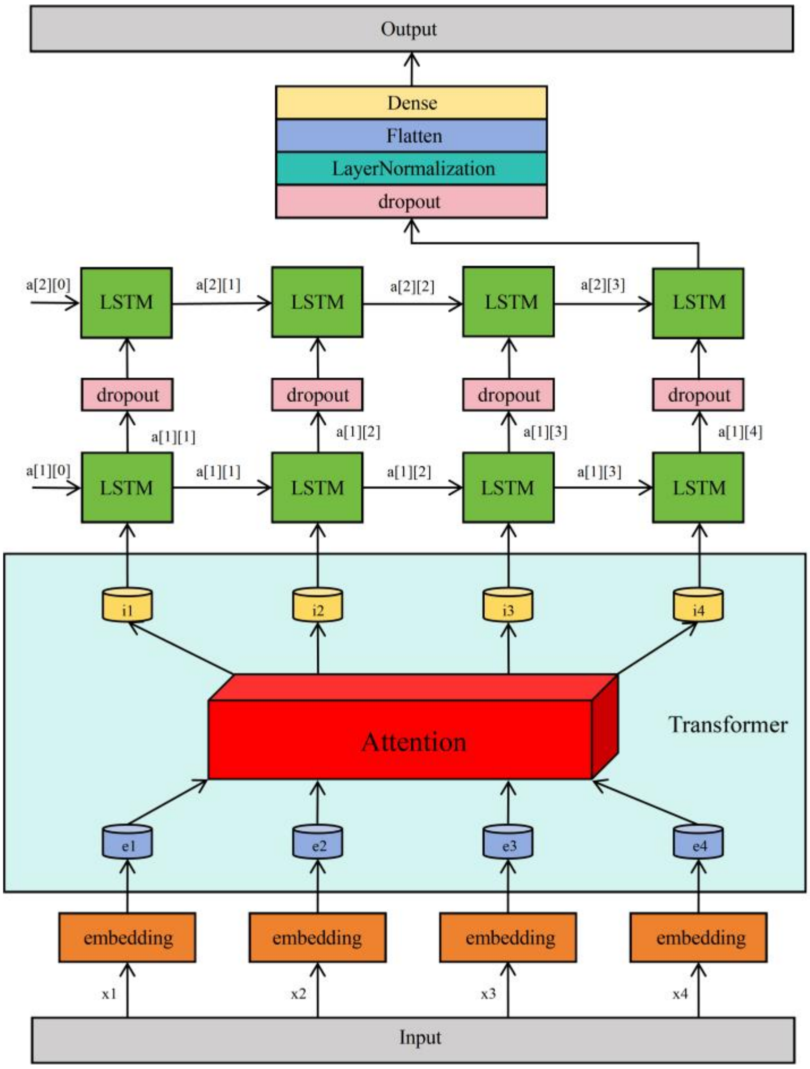

Fig. 3. LSTM-Transformer Model framework

As illustrated in Fig. 3, the Attention module assigns importance weights[20] to the past input time series. From the perspective of the neural network architecture, this mechanism effectively avoids the "Long term dependency" problem caused by the loss of past temporal features[21].

3 Result

3.1 Experiment Results and the NPQ Model Mathematical Expression

Hydraulic experiments on the pVAD are conducted under various experimental conditions (different motor speeds, pressures, and flow rates). For each condition, several experiments are performed, and the average value of these experiments is recorded as the experimental data for that condition, which is then plotted on the P-Q curve below, as in Fig. 4.

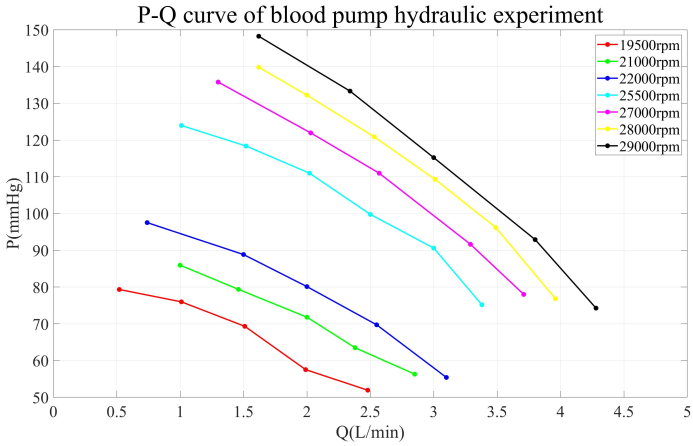

Fig. 4. Hydraulic Experiment P-Q Curve of the pVAD

As shown in Fig. 4, experimental data for pVADs under multiple operating conditions are successfully measured. First, this hydraulic experiment data provides a significant reference value for future applications of the pVAD in animal experiments and clinical trials. More importantly, by substituting the data from the experiments into Equation 3, the coefficients a and b are solved. The NPQ Model mathematical expression is as follows:

$$N = 117.4P + 551Q^2 + 10270 \tag{5}$$

where N represents the motor speed, measured in r/min. P represents the pressure provided by the pump, measured in $mmHg$. Q indicates the flow rate delivered by the pump, measured in L/min. All coefficients in the model are accompanied by units. The unit for coefficient 117.4 is $r/(mmHg \cdot min)$, the unit for coefficient 551 is $(r \cdot min)/L^2$, and the unit for coefficient 10270 is r/min.

3.2 Pressure Prediction Results of the NPQ Model

The NPQ model is applied to three new pVAD hydraulic experiments for validation. In this validation experiment, to simulate clinical requirements, combinations of the desired pressure and flow are input into the NPQ model at different motor speeds to determine whether the pVAD can deliver results that are close to the desired pressure.

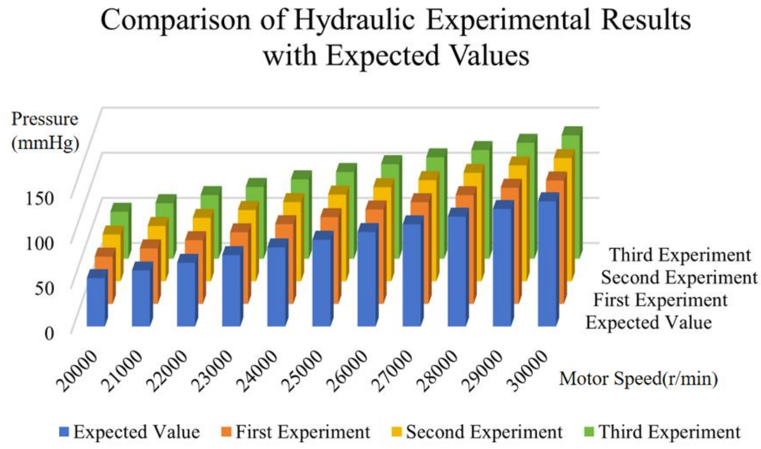

Fig. 5. Pressure comparison visualization for three validation experiments

The results of the three hydraulic experiments are statistically analyzed. The maximum error between the pressure values calculated by the NPQ model and the desired pressure values is only 2.15 $mmHg$. This result demonstrates that the NPQ model possesses excellent performance in the accuracy of pVAD output values.

3.3 Time Prediction Results of the LSTM-Tranformer Model

The LSTM, GRU, and LSTM Transformer models are respectively employed to predict the characteristic points of pulsation time for a comparative study. The maximum prediction error of each experimental group, defined as the maximum absolute value of the difference between the true value and the predicted value, is selected as the evaluation metric[3]. The results are presented in Table 1:

Table 1. Comparison of maximum errors among three models(unit: ms)

	GRU	LSTM	LSTM-Transformer
Experiment 1	4.7	3.8	2.8
Experiment 2	5.2	4.1	3.4
Experiment 3	4.6	3.9	3.3

As shown in Table 1, the new LSTM Transformer method demonstrates a significant improvement in the maximum prediction error for pulsation characteristic time points compared with the two traditional methods: GRU and LSTM. To a certain extent, this reflects the importance of incorporating the Attention module to enhance the prediction accuracy of pVADs, which may be a result of the Attention module addressing the long term dependency problem. Furthermore, when compared with the maximum prediction error of 5 ms reported in previous studies[4], the prediction results of the LSTM Transformer across multiple experimental datasets are also significantly superior to results in previous research.

Furthermore, to evaluate the robustness of the LSTM Transformer Model, the data from Experiment 1 is subjected to two distinct treatments: the addition of varying degrees of noise and the reduction of the dataset scale. These treatments are employed to simulate scenarios in the real world characterized by poor data quality[21]. The purpose is to observe whether the maximum prediction error of the LSTM Transformer model will undergo significant changes.

Table 2. Robustness Testing of the Model under Different Data Scenarios

Noise level (%)	Maximum error (ms)	Data reduction(%)	Maximum error (ms)
0	2.8	0	2.8
5	2.8	5	3.0
10	3.0	10	3.6
20	3.1	20	4.9

As shown in Table 2: (1)the maximum prediction error of the LSTM Transformer Model does not exhibit a significant increase when facing noise levels within 10%. This suggests that the model is expected to maintain robust prediction performance even with clinical data that may contain a moderate amount of noise. (2)Compared with the noise level, the reduction in dataset scale has a more pronounced impact on the maximum prediction error of the model. When the dataset scale is reduced by 20%, the maximum prediction error of the LSTM Transformer model nearly doubles compared with the original error, indicating that the model is relatively sensitive to variations in data volume. Therefore, in future potential clinical application scenarios, it is essential to fully ensure an adequate volume of clinical data for model training.

4 Conclusion

This study has primarily achieved three contributions: (1)A hydraulic experimental platform for pVADs is constructed, and comprehensive hydraulic experiments are conducted under multiple operating conditions and multidimensional variables. P-Q curves are plotted, and real-world data reflecting the physical characteristics of pVADs are obtained. The construction logic of the hydraulic experimental platform and the collection of multiple physical quantities under various operating conditions provide a comprehensive and feasible framework for the future preliminary research of physical characteristics in other left ventricular assist devices. (2)The NPQ Model, a mathematical relationship between the three key physical variables of pVAD motor speed, pressure, and flow, is derived based on equations such as the Bernoulli equation. This model reveals that for a given pVAD, motor speed has a linear relationship with pressure and a quadratic relationship with flow. It successfully addresses the problem of hemodynamic numerical accuracy in the pulsatile function of pVADs. (3)An LSTM Transformer model is constructed to predict the pulsation characteristic time points. At the structural level of the neural network architecture, this model effectively solves the “Long term dependency” problem inherent in traditional time series methods. The prediction results of this model are significantly superior to those of traditional methods and demonstrate a certain degree of robustness.

Although the above workflow is implemented in this study, several limitations remain. First, the number of validation experiments is relatively limited. More hydraulic tests, animal experiments and clinical trials are required for further verification in future work. In addition, the current model has not been integrated into a digital twin framework tailored to real-world scenarios, such as patient-specific conditions and intraoperative abnormal events. These represent promising directions for future development of this work.

In summary, the NPQ Model and LSTM Transformer model proposed in this study have been validated through multiple hydraulic experiments. They hold significant foundational importance for the future realization of pVAD pulsatile functions and the development of cardiac digital twins.

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