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Validation and Refinement of Fluid Dynamics Models for Vacuum Pressure Relief Valves Based on Data Analysis

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ABSTRACT

In the advancement of modern industry and technology, vacuum pressure relief valves play a pivotal role across various fields. Traditional physical experimental approaches face limitations such as high costs, limited flexibility, and incomplete data collection. This study leverages a virtual simulation platform to focus on the validation and refinement of fluid dynamics models for vacuum pressure relief valves. By innovatively employing a multi-software integrated modeling and simulation strategy, the study optimizes models through data-driven analysis and establishes a dynamic adaptive correction mechanism. Based on the operating principles of vacuum pressure relief valves and fluid dynamics theory, the research involves model construction, simulation experiment design, and data collection. Techniques such as data correlation analysis and error metric evaluation are employed for model validation, and targeted correction strategies are developed to address error sources. The corrected model is further validated following intelligent parameter optimization. Results demonstrate significant improvements in key performance indicators, providing robust technical support for advancements in the vacuum pressure relief valve domain.

1. INTRODUCTION

1.1 Research background and significance

With the rapid development of modern industry and science and technology, vacuum pressure relief valves, as critical components in many fields, play an indispensable role. Whether in high-end industries such as semiconductor manufacturing, aerospace, chemical and pharmaceutical sectors, or in general industrial production and laboratory research scenarios, precisely controlling the pressure within vacuum systems is of great importance for ensuring the stability of production processes, improving product quality, and ensuring the accuracy of experimental data.

Traditional research methods for vacuum pressure relief valves mainly rely on physical experimental testing. Although this approach can intuitively reflect the performance of the valves under actual working conditions, it also has many limitations. On the one hand, building a real experimental platform often requires significant manpower, material, and time costs. Every step, from purchasing and installing equipment to preparing samples and simulating working conditions, requires meticulous operations. Moreover, whenever experimental conditions need to be adjusted, such as changes in pressure range, fluid medium, or temperature environment, the entire experimental platform must be reconfigured, which results in poor flexibility. On the other hand, physical experiments lack comprehensiveness in data collection. Limited by the positioning and quantity of sensors, it is difficult to obtain detailed information on the flow field within the valve, making it challenging to accurately capture transient phenomena and microscopic flow mechanisms [1].

With the vigorous development of computer technology and numerical simulation methods, virtual simulation platforms have emerged, opening new avenues for the research of vacuum pressure relief valves. Through virtual simulation, it is possible to construct models in a computer environment that closely approximate real physical scenarios [2], allowing the flexible setting of diverse boundary conditions and working parameters. This approach enables rapid simulation of valve performance under different working conditions, greatly improving research efficiency. At the same time, the massive amount of data generated by virtual simulations, combined with advanced data analysis techniques, allows for in-depth exploration of the complex fluid dynamics principles within valves. This can precisely identify the key factors affecting performance, providing solid data support for model optimization and correction, and ultimately promoting the application of vacuum pressure relief valves in engineering practices towards greater efficiency and reliability [3, 4].

This study focuses on fully utilizing the convenience provided by virtual simulation platforms and systematically applying data analysis methods to scientifically validate and accurately refine the fluid dynamics model of vacuum pressure relief valves. It aims to address the shortcomings of traditional research methods and inject new vitality into the technological development of related fields.

1.2 Research innovations

The innovations of this study are mainly reflected in the following three aspects:

(1) The adoption of a multi-software integrated modeling and simulation strategy, leveraging the advantages of various specialized software. CAD software is used for precise valve modeling, CFD software is employed for flow field simulation calculations, and MATLAB and other software are applied for data analysis and post-processing of models. This approach fully utilizes the strengths of each software in different stages, breaking the functional limitations of a single software, and achieving efficient end-to-end processing from model construction to result analysis.

(2) A data-driven model optimization method. Unlike traditional approaches relying on small-sample experimental validation and model refinement, this study uses the massive data generated by virtual simulations. Advanced technologies such as data mining and machine learning are employed to deeply explore the hidden physical laws behind the data and accurately identify the key factors affecting valve performance. This provides a comprehensive and scientific basis for model optimization, making the process more intelligent and precise.

(3) The establishment of a dynamic adaptive model refinement mechanism. Considering the variability of working conditions for vacuum pressure relief valves in practical engineering, the model refinement system established in this study is not static but can adjust refinement strategies in real time based on validation results under different working conditions. The model dynamically adapts to complex changes in conditions, such as pressure transients, fluid medium switches, and valve wear, maintaining high prediction accuracy and providing strong assurance for the reliable application of vacuum pressure relief valves in complex and variable engineering environments.

1.3 Research technical roadmap

The technical roadmap of this study is shown in Figure 1.

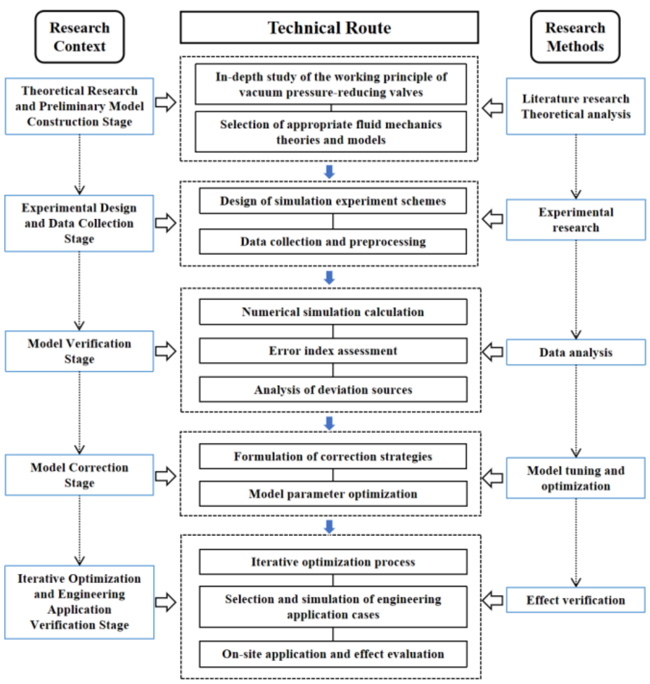


Figure 1. Research technical roadmap

2. OPERATING PRINCIPLES OF VACUUM PRESSURE RELIEF VALVES AND FUNDAMENTALS OF FLUID DYNAMICS

2.1 Structural analysis of vacuum pressure relief valves

A typical vacuum pressure relief valve consists of core components such as the valve body, valve core, spring, and sealing elements. Taking a direct-acting pressure relief valve as an example, a three-dimensional exploded view (Figure 2) fully presents the structural components. The valve body serves as the casing that houses the internal components and connects the pipeline. The valve core moves flexibly in response to pressure changes, with its head shape significantly influencing flow characteristics. The spring provides a preload force, working in coordination to regulate pressure, while the sealing elements ensure no leakage occurs. The materials of each component are selected based on the severity of working conditions. For instance, high-temperature environments require high-temperature-resistant alloys while also considering the feasibility of mechanical processing to ensure excellent overall performance. For different structural types, such as pilot-operated pressure relief valves, a pilot valve is introduced to precisely control the main valve opening. This type shows advantages in high-pressure differential and large-flow scenarios, with fast response speed and high adjustment accuracy.

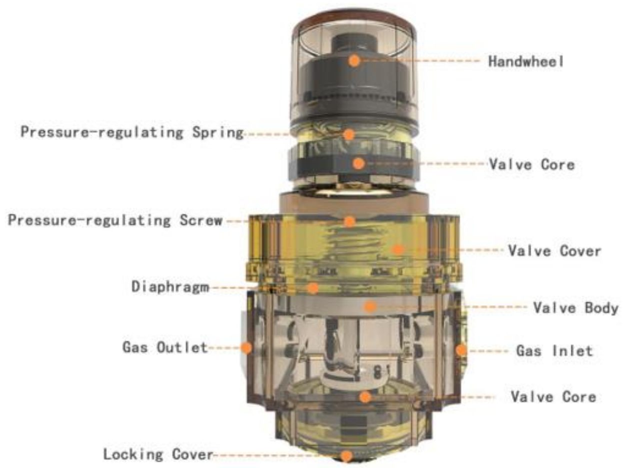


Figure 2. 3D exploded view of the vacuum pressure relief valve

2.2 Analysis of operating principles

Based on gas dynamics principles, when the inlet pressure acts on the valve core, it overcomes the spring force to push the valve core, thereby opening the pressure relief channel. The intake, regulation, and exhaust processes can be described as follows: At the initial stage of intake, the pressure overcomes the static friction of the valve core, allowing a small airflow to pass through. During the regulation stage, the valve core maintains a dynamic balance and adjusts the opening degree according to inlet pressure fluctuations to stabilize the outlet pressure, accurately controlling based on the force balance equation of the valve core ($Fp - Fs - Ff = ma$, where Fp is the fluid pressure, Fs is the spring force, Ff is the frictional force, m is the mass of the valve core, and a is the acceleration). During exhaust, when the inlet pressure drops sharply, the spring force resets the valve core to close the valve. Comparing gas and liquid mediums, liquids, due to their high viscosity and near-incompressibility, exhibit significantly different flow states within the valve, such as laminar flow being more likely, different boundary layer separation characteristics, and complex, variable flow patterns in multiphase flow scenarios involving gas-liquid mixtures. These characteristics pose substantial challenges for modeling.

2.3 Application of core fluid dynamics theories

The continuity equation ($\rho 1 v 1 A 1 = \rho 2 v 2 A 2$), Bernoulli equation ($P1 + \frac{1}{2}\rho v1^2 + \rho g h1 = P2 + \frac{1}{2}\rho v2^2 + \rho g h2$), and momentum equation are indispensable in the flow field analysis of vacuum pressure relief valves [5]. Combined with local simplifications in the valve, a flow formula suitable for the valve port contraction section is derived ($Q = CdA0\sqrt{\frac{2\Delta P}{\rho}}$, where Cd is the flow coefficient, $A0$ is the valve port area, ΔP is the pressure difference between inlet and outlet, and ρ is the fluid density). Turbulence models [6], such as the standard k-ε model, are introduced, with equation being $\frac{\partial(\rho\kappa)}{\partial t} + \frac{\partial(\rho\kappa vi)}{\partial xi} = \frac{\partial}{\partial xj}[(\mu + \frac{\mu t}{\sigma k})\frac{\partial k}{\partial xj}] + Gk - \rho\varepsilon$, where k is the turbulent kinetic energy, ε is the dissipation rate of turbulent kinetic energy, Gk is the turbulent energy production term, μ is dynamic viscosity, μ_t is turbulent viscosity, and σk is the Prandtl number of turbulent kinetic energy), to capture complex flows in high turbulence regions downstream of the valve core. Boundary layer theory explains low-speed flow dominated by viscous forces near the wall, guiding precise parameter settings for numerical simulations.

3. CONSTRUCTION OF THE FLUID DYNAMICS MODEL FOR VACUUM PRESSURE RELIEF VALVES

3.1 Construction of a 3D model of vacuum pressure relief valves

The 3D model of a vacuum pressure relief valve can be constructed using professional 3D modeling software (such as SolidWorks) for detailed modeling of the valve body. This provides a comprehensive 3D perspective of the valve body structure. The valve body is shaped like a relatively regular cylinder with a complex and precise internal cavity. Through accurate dimension settings, the fluid can flow smoothly within. As shown in Figure 3.

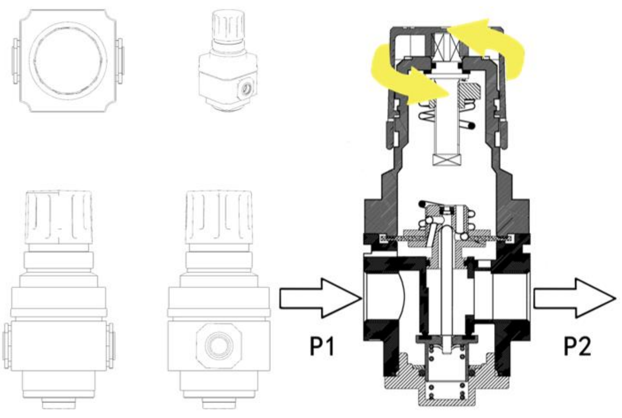


Figure 3. 3D model of a vacuum pressure relief valve

3.2 Selection of fluid dynamics models

Based on the Navier-Stokes equation system ($\rho(\frac{\partial\mu}{\partial t} + u.\nabla u) = -\nabla p + u\nabla^2 u + f$), and considering the characteristics of the actual working conditions of vacuum pressure relief valves, appropriate turbulence models are carefully chosen [6]. For high Reynolds number turbulent regions within the valve and areas with significant anisotropy in the flow field, the Reynolds Stress Model is preferred, as it accurately captures turbulent fluctuation correlation terms. Boundary conditions are precisely set according to experimental conditions. For example, the inlet pressure is set to vary stepwise from 10 kPa to 100 kPa under actual conditions, and the temperature range is adjusted between 25°C and 150°C [7]. Wall boundary conditions are carefully considered, with surface roughness parameters set based on measured roughness values of the valve body surface. This ensures that the mathematical model closely matches real working conditions, laying a foundation for accurate simulations.

3.3 Optimization of model solving strategies

In the CFD solver, choosing an appropriate solution algorithm is crucial [3]. The pressure-based algorithm is suitable for most subsonic flows, while the density-based algorithm is supplemented for enhanced stability in locally supersonic flow regions [8]. Iterative convergence criteria are finely set, with residual control standards set between 10^{-5} and 10^{-6}. Simultaneously, key physical quantities such as inlet and outlet flow and pressure convergence are monitored to ensure a highly efficient and stable solving process, significantly reducing computation cycles [9]. During the numerical calculation process, the built-in monitoring function of the solver is used to track the iterative convergence trends of key physical quantities such as pressure, flow, and velocity in real-time. Computational resource allocation is dynamically adjusted, and a complete computation log is recorded to provide accumulated data and experience for in-depth analysis of simulation results and model optimization.

4. SIMULATION EXPERIMENT DESIGN AND DATA COLLECTION

4.1 Experimental plan design

A multi-dimensional experimental plan is developed to comprehensively cover different inlet pressure ranges (from coarse vacuum at 1000 Pa to ultra-high vacuum at 10^{-4} Pa), a wide flow rate range (covering micro flow rates of 0.1 L/min to the rated maximum flow rate of 10 L/min), and diverse temperature conditions (from room temperature of 25°C to special industrial high temperatures of 200°C), accurately simulating actual application scenarios in industries such as semiconductors, photovoltaics, and chemicals. The valve opening adjustment strategy is precisely planned, combining an electric actuator to implement various opening adjustment methods, including equal-step, logarithmic-step, and random-step adjustments. This deeply explores the dynamic changes in valve flow and pressure characteristics with the valve opening. Multiple repeat experiments (no less than 8 times) are set up for each working condition, and statistical methods are used to strictly control experimental errors to ensure the representativeness and reliability of the data. The entire experimental design process is shown in Figure 4.

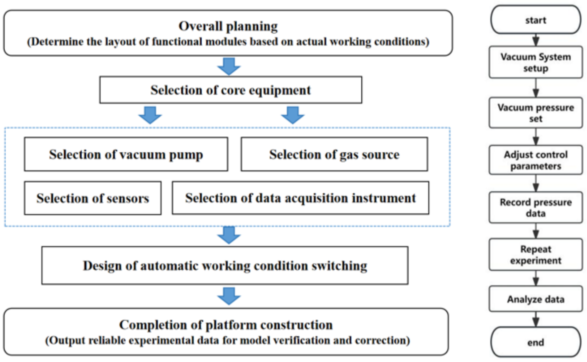


Figure 4. Simulation platform setup and experimental process

4.2 Data collection and processing

In the virtual simulation experiments of the vacuum pressure-reducing valve, multiple types of data must be collected to comprehensively reflect its performance. Pressure data covers key positions inside the valve, such as the throttling port, valve chamber, and inlet and outlet points, to analyze pressure drop and pressure distribution uniformity. Velocity data includes the magnitude and direction of fluid flow in various regions, aiding in understanding flow paths, potential backflow, and vortices. Flow rate data, involving the inlet and outlet flow rates, evaluates flow regulation characteristics. Displacement and force data of the valve core are crucial for investigating the dynamic response and stability of the valve.

Using the built-in data acquisition tools in simulation software, the sampling frequency is set at 0.01 seconds per interval to capture transient changes in flow field parameters. For steady-state simulations, data is collected continuously for 100–200 points after the flow field stabilizes, averaging the values to reduce random errors. For transient simulations, data is collected throughout the process to record dynamic changes during valve opening or sudden changes in operating conditions.

The collected data needs preprocessing to exclude obvious outliers caused by factors such as mesh distortion or non-convergence. Filtering algorithms are applied to remove high-frequency noise, using methods such as moving averages or low-pass filtering to smooth the data while preserving trend features. During feature extraction, pressure fluctuation amplitudes and frequencies are calculated to reflect the intensity and periodicity of pressure fluctuations. Turbulence characteristics are quantified by calculating turbulence intensity and Reynolds stress tensor components. Additionally, the peak, mean, and standard deviation of valve core displacement are analyzed to evaluate its motion stability, providing precise data for subsequent model validation and refinement [10].

5. MODEL VALIDATION BASED ON DATA ANALYSIS

5.1 In-depth correlation analysis of data

Using multivariate statistical methods such as Pearson correlation coefficients and Spearman rank correlation coefficients, a comprehensive analysis of experimental and numerical simulation data is performed for key variables like inlet and outlet pressure, flow rate, and velocity [11, 12]. The linear or non-linear correlation degree is accurately quantified, and high-resolution scatter plots are drawn to visually present data distribution patterns and trends. For example, under a specific inlet pressure-flow condition, a Pearson correlation coefficient of 0.95 indicates a high linear correlation between simulation and experimental data. However, under extreme high-temperature conditions, the correlation for some variables drops sharply to 0.7, suggesting potential model deviations under such conditions. Based on the correlation analysis results, the model's consistency with actual conditions is deeply assessed. If weak correlation regions are identified, the sources of deviations are investigated by combining fluid dynamics principles and experimental details, such as inappropriate model geometric simplifications or inaccuracies in turbulence simulation.

5.2 Precise calculation and evaluation of error metrics

A set of rigorous error metrics is defined and calculated, including root mean square error (RMSE), mean absolute error (MAE), relative error (RE), and Nash efficiency coefficient (NSE), to measure the deviation between model predictions and experimental values from various dimensions. For instance, the RMSE is calculated as $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(yi-\hat{y}i)^2}{n}}$, where yi represents experimental values, $\hat{y}i$ denotes simulation values, and n is the number of data points. Based on statistical results of error metrics, error bar charts and line graphs are plotted for different operating conditions to intuitively compare the magnitude and fluctuation trends of model errors. Significant error conditions are precisely identified, and the root causes of errors are thoroughly explored to provide targeted insights for model refinement [13].

5.3 Analysis of model validation results

Integrating the conclusions from correlation analysis and error metric evaluations, a comprehensive and in-depth discussion is conducted on the validation effectiveness of the fluid dynamics model in simulating the operating process of the vacuum pressure-reducing valve. The reliability and limitations of the model in describing various physical quantities under conventional and extreme operating conditions are clarified.

In the comparison between the simulation data and actual data of the vacuum pressure relief valve: For the flow coefficient, in most operating conditions, the simulation calculation values have a deviation of less than 5% compared to the theoretical formula values or empirical data. Under extreme operating conditions, the deviation reaches up to 8%, which is due to the failure of the simplified assumptions in the traditional theoretical formulas caused by high viscosity fluids and very small valve core openings. For the pressure loss coefficient, the deviation is generally controlled within 10%, but it increases to 15% under transonic conditions, due to the model's difficulty in accurately describing the complex changes in transonic flow. The valve outlet pressure stability index highly matches the actual data under steady-state conditions, with fluctuation amplitude controlled within ±2%

of the set value. However, during dynamic condition switching, overshoot or undershoot occurs, with the maximum overshoot reaching 5% of the set value.

In summary, the model demonstrates high reliability under conventional conditions. However, problems arise under extreme conditions and during dynamic transient processes. Improvements are needed in handling special flow states, optimizing the valve core's dynamic response model, and enhancing the accuracy of transient simulations to improve the model's accuracy and reliability.

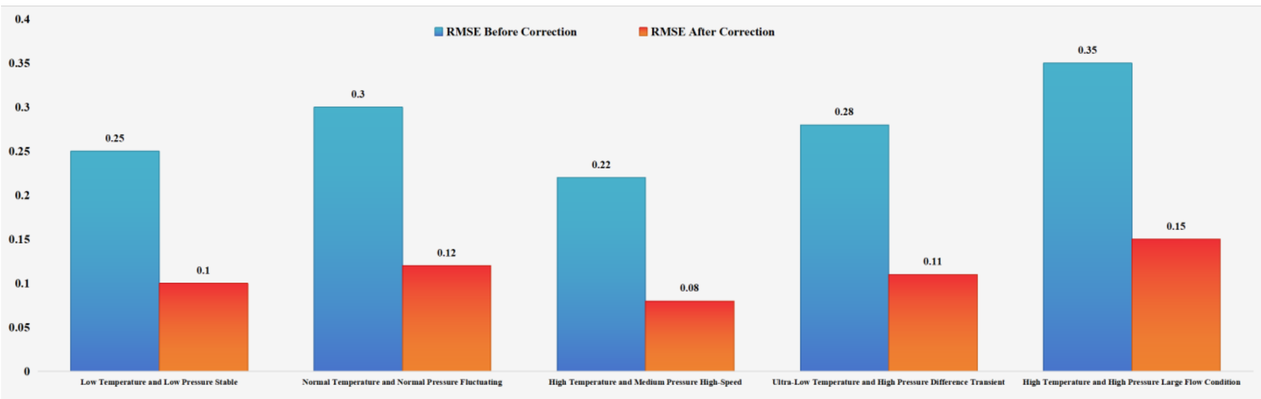
6. MODEL CORRECTION STRATEGIES AND IMPLEMENTATION

6.1 Analysis of error sources

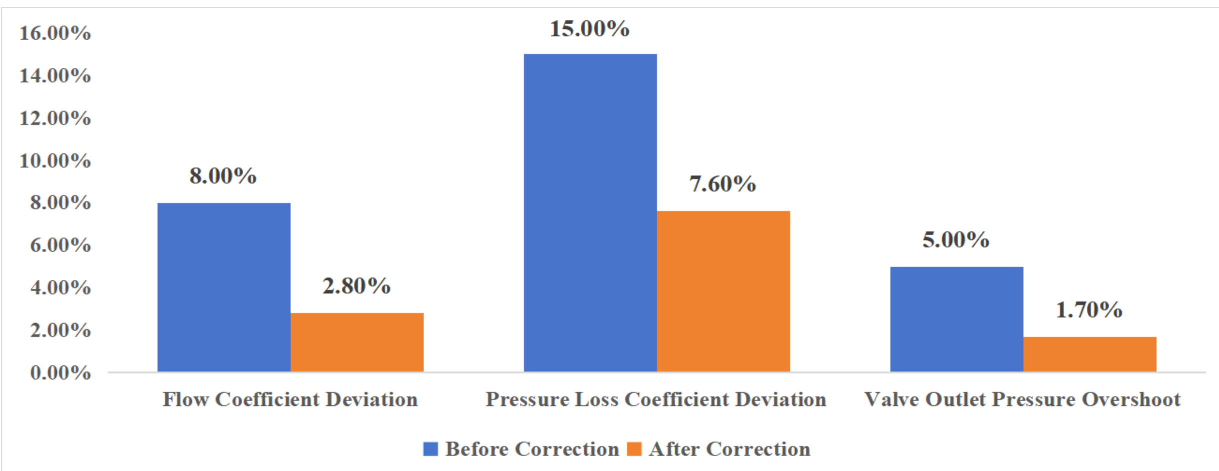
Based on the diagnostic of model verification results and deviation analysis, a systematic correction strategy is formulated for different types of root cause problems. If excessive geometric simplification is found in the model, the original design drawings should be carefully reviewed, and key structural details should be appropriately restored, such as small fillets and gap channels, followed by remeshing for recalculation. If the turbulence model's applicability is inadequate, extensive research should be conducted on new improved turbulence models [14], such as the separation vortex model, or optimize the existing model parameters based on experimental data, using genetic algorithms to optimize the constants in the k-ε model, thereby enhancing the model's ability to simulate complex turbulence. A data-driven correction concept should be established, introducing machine learning algorithms to create an intelligent mapping from experimental data to model correction parameters. Various machine learning algorithms should be compared in the model correction scenario, and a backpropagation neural network architecture should be selected due to its powerful nonlinear mapping capability, which can efficiently capture complex relationships in the data.

6.2 Intelligent optimization of model parameters

The preprocessed experimental data is divided into training, validation, and test sets in appropriate proportions. The selected machine learning algorithm is driven by the training set data [12], with the core objective of minimizing model prediction errors. The algorithm iteratively learns the model correction parameters, and the validation set dynamically monitors the risk of overfitting, adjusting algorithm hyperparameters in a timely manner. After multiple rounds of high-intensity training and optimization, the optimal model correction parameters are extracted and seamlessly integrated into the original fluid dynamics model. The model equation coefficients, boundary condition parameters, or turbulence model constants are precisely updated, reshaping the high-precision corrected model [15]. For example, correction coefficients for a turbulence model obtained through neural network training reduce prediction errors by 30% under high Reynolds number conditions.



(a)



(b)

Figure 5. (a) RMSE values before and after correction; (b) Coefficient deviation comparison before and after correction

6.3 Verification of the corrected model

To comprehensively evaluate the effectiveness of the corrective measures, a systematic validation of the fluid dynamics model for the vacuum pressure reducing valve was conducted [16]. In terms of the flow coefficient, simulations were re-conducted under various working conditions, comparing the pre- and post-correction model calculations with theoretical formula derivations or empirical data. After correction, the deviation of the flow coefficient under extreme conditions such as high-viscosity fluids and minimal valve openings was significantly reduced, dropping from a maximum of 8% to within 3%, achieving accuracy comparable to that of conventional working conditions. This strongly demonstrates the effectiveness of parameter optimization and structural adjustments in improving the accuracy of complex flow state simulations.

For the validation of the pressure loss coefficient, emphasis was placed on testing special conditions such as transonic flow. The deviation between the corrected model's predicted pressure loss and actual energy loss data under transonic conditions was significantly reduced from approximately 15% to within 8%. This improvement highlights the model's enhanced handling of fluid compressibility changes, shockwaves, and other nonlinear phenomena, enabling a more precise reflection of the valve's internal flow resistance characteristics.

The validation of downstream pressure stability focused on dynamic working conditions during transitions. Simulations were performed for scenarios such as sudden changes in inlet pressure and rapid flow adjustments, monitoring the downstream pressure change curves. The corrected model effectively suppressed overshoot or undershoot phenomena in downstream pressure during dynamic transitions, reducing the maximum overshoot from up to 5% of the set value to within 2%. The characteristics of fluctuations, such as amplitude and frequency, also showed improved consistency with actual experimental or engineering operation data, further demonstrating the model's optimization of valve dynamic response characteristics. The verification data results are shown in Figures 5(a) and 5(b).

In summary, the corrected model shows significant improvements in all key performance indicators and greatly enhances conformity with actual working conditions. However, there are still areas for refinement, such as predicting accuracy under extreme complex conditions like multiphase flow and high-temperature/high-pressure coupling. Future research could further explore the depth and breadth of multi-physics coupling, optimize the model's dynamic adaptability, and introduce more advanced turbulence models and numerical algorithms to continuously improve the model's universality and accuracy, meeting the demands of increasingly complex engineering applications for vacuum pressure reducing valves.

7. CONCLUSIONS AND OUTLOOK

7.1 Research summary

The full process of validation and correction of the vacuum pressure reducing valve's fluid dynamics model based on data analysis encompasses key stages such as theoretical foundation, model construction, experimental design, data analysis, model optimization, and engineering verification. Systematic achievements at each stage include the construction of a high-precision model, collection of massive experimental data, extraction of critical data patterns, implementation of precise model corrections, and successful application to engineering cases. The study emphasizes the core challenges addressed, such as overcoming the limitations of traditional model validation, resolving the root causes of model deviations, and pioneering data-driven model optimization pathways, providing strong theoretical and practical support for technological innovation in vacuum pressure reducing valves and the vacuum technology field.

7.2 Research limitations and outlook

Research Limitations: Although significant progress has been made in the validation and correction of the fluid dynamics model for vacuum pressure reducing valves, there are still areas for improvement, such as model accuracy under extreme conditions, real-time dynamic response, multiphysics coupling simulations, limitations of data-driven methods, and computational resource consumption. For example, prediction accuracy under extremely complex conditions (e.g., multiphase flow and high-temperature/high-pressure coupling) still requires enhancement. The model's responsiveness and accuracy during dynamic condition transitions also need further improvement. Additionally, the current study focuses mainly on fluid dynamics while neglecting the comprehensive consideration of multiphysics effects such as thermodynamics and electromagnetism. The data-driven model correction relies on high-quality experimental data, and obtaining datasets that comprehensively cover various conditions is challenging. High-precision numerical simulations and large-scale data analysis require substantial computational resources, limiting the model's application scope.

Future Outlook: Future research will focus on deepening modeling for extreme conditions, developing specialized turbulence and multiphase flow models for complex flow phenomena, enhancing dynamic response simulations, exploring real-time simulation technologies and online monitoring methods to improve transient prediction capabilities and response speed, constructing multiphysics coupling models, and integrating models across domains for full-condition precise simulation. The fusion of data-driven and physical models will be advanced, leveraging big data and machine learning technologies to uncover hidden patterns while ensuring model interpretability and generalization capabilities. Computational resource management will be optimized by exploring efficient parallel and distributed computing methods to reduce time costs. Application scenarios will be expanded to include new material development, intelligent manufacturing, energy conversion, and other fields, driving technological innovation and development. These efforts aim to achieve greater breakthroughs in theoretical innovation and technological application, contributing to the progress of vacuum pressure reducing valves and related fields.

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