

Digital Twin Modeling and Simulation Verification of a Differential Pressure Power Generation System

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Abstract: To address the high risk of abnormal-condition handling and the limited intuitiveness of conventional two-dimensional configuration monitoring in natural gas transportation, this paper proposes a digital twin simulation method for differential pressure power generation. Three-dimensional models of the generator unit, valves, and pipelines are constructed, and interactive functions such as gas-flow particle animation, valve-opening pop-up windows, equipment labels, and audible/visual alarms are developed. Equal-percentage, linear, and quick-opening flow characteristics are introduced into a four-valve pipeline coupling model. The virtual model is driven by simulation data, and an incremental PI load-tracking controller, four fault-injection scenarios, and configurable thresholds are designed to form an operation-control verification framework of injection, detection, alarm, handling, and recovery. Simulation results show that adjusting valve openings changes pipeline pressure, flow rate, and power generation; the four faults produce corresponding responses; and the PI controller converges the actual power to within $\pm 5\%$ of the target within 30 s.

Keywords: differential pressure power generation; digital twin; multi-valve coupling simulation; Web 3D visualization; fault injection; PI control

1. Introduction

Natural gas is an important clean energy source in China's energy mix. During transmission and pressure regulation, a large amount of pressure energy is dissipated through throttle valves. Differential pressure power generation recovers this energy using an expander and converts it into electricity, providing significant energy savings under the dual-carbon goal [1-4]. However, differential pressure power generation systems still face challenges such as distributed equipment, high risks in abnormal-condition handling, and the limited ability of conventional two-dimensional configuration interfaces to represent equipment status and pipeline flow, which restricts operational efficiency and deployment.

Digital twin technology provides a new approach to these problems and has been applied to power equipment condition monitoring [5-7], rotating machinery fault diagnosis [8-9], process-industry closed-loop control [10], and oil and gas pipeline integrity management [11-12], providing a reference for the digital operation of differential pressure power generation systems. In power generation, Sun [13] proposed a condition-monitoring method for hydro-generator units; Li et al. [14] developed a five-dimensional digital twin framework for power electronic devices, enabling condition monitoring, temperature assessment, and lifetime prediction.

In gas pipeline networks, Chen et al. [15] integrated digital twin and deep learning technologies to build a pipeline leak detection system, achieving 3D visualization, intelligent detection, and condition monitoring. Existing studies mainly focus on determining whether equipment is currently abnormal, but provide limited support for valve adjustment, load tracking, and post-fault handling. Therefore, a digital twin environment with a physics-based simulation kernel and intuitive 3D interaction is needed for low-risk control-strategy validation, fault handling, and operation monitoring.

To address these issues, this paper takes a natural gas pressure regulating station as the research object, builds a four-valve pipeline coupling simulation model, and uses model-generated data to drive the virtual model. Web 3D rendering is used to visualize equipment status and pipeline flow.

Incremental PI load tracking, four fault-injection scenarios, and threshold alarm linkage are integrated to form an injection-detection-alarm-handling-recovery verification framework, providing an interactive environment for control-strategy validation and fault handling.

2. Overall Architecture Design of the Digital Twin System

This chapter introduces the overall architecture and data flow of the digital twin system for differential pressure power generation, providing a basis for the subsequent physical model, 3D scene, and control-function design.

2.1 System Architecture Design

The system adopts a four-layer architecture consisting of physical, data, model, and visualization layers (Fig. 1). The physical layer describes the four-valve pipeline, turbine expander, generator, and downstream network using a virtual model. The data layer maintains a 500-record historical data queue and supports JSON/CSV export and a 1 Hz clock driver. The model layer includes the four-valve coupling model, PI controller, alarm module, and fault-injection module, and calculates turbine work, power generation, and equipment states. The visualization layer is built with Vue 3 and Three.js and consists of a data panel, 3D scene, and control panel.

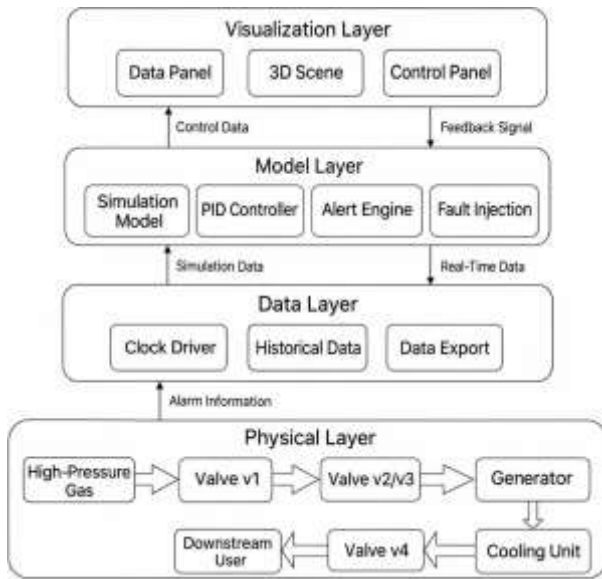


Figure 1 System architecture diagram

The model layer generates 15 operating parameters per second, including inlet pressure, outlet pressure, and pressure difference; new data are inserted at the head of the queue and removed from the tail. The model is independent of field sensors and can run without a physical entity. The PI controller adjusts the openings of V1 and V3 according to the power error. The alarm engine monitors generator

temperature, bearing vibration, inlet pressure, and outlet pressure, and triggers sound alarms, 3D flashing, and alarm records when thresholds are exceeded.

The data panel displays real-time parameters using gauges and trend curves. The 3D scene provides valve highlighting, CSS2D labels, gas-particle flow, and alarm flashing. The control panel supports start/stop control, valve adjustment, operating-condition configuration, load-target setting, fault injection, and threshold adjustment. Model data are pushed to the visualization layer through Pinia, while operator commands drive the simulation in the reverse direction, forming a closed loop of data-driven display and command-driven simulation.

3. Physical Model and Simulation Algorithm

This chapter establishes the physical model of the differential pressure power generation system, including the process flow, valve characteristics, pipeline coupling solution, and turbine and equipment-state calculations.

3.1 Process Flow

The system uses a four-valve pipeline topology, as shown in Fig. 2. In normal operation, V2 is closed; natural gas enters the turbine through V1 and V3, expands to drive the generator, and is discharged to the downstream network through V4, achieving both pressure reduction and power generation. During maintenance or faults, V2 opens to bypass the generation branch and ensure continuous gas supply.

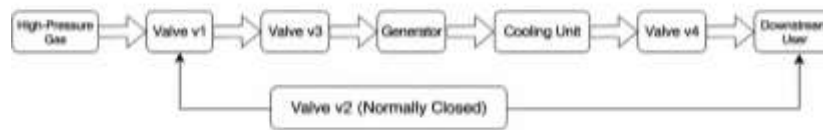


Figure 2 Four-valve pipeline topology

3.2 Valve Flow Characteristic Modeling

Valve opening determines the flow distribution among branches. The mass flow through a single valve and the pressure difference satisfy Eq. (1), where $C_v(x)$ is the flow coefficient and x is the valve opening.

$$\dot{m} = C_v(x) \sqrt{\Delta p} \quad (1)$$

In Eq. (1), $\dot{m}$ is the mass flow rate (kg/s), Δp is the pressure difference across the valve (MPa), and x is the valve opening (0-1). The flow coefficient can be expressed by Eq. (2), where $C_{v,max}$ is the fully open flow coefficient and $f(x)$ is the flow characteristic function.

$$C_v(x) = C_{v,max} f(x) \quad (2)$$

Common flow characteristics include linear, quick-opening, and equal-percentage types. The linear characteristic is given by Eq. (3), in which the flow coefficient is proportional to the valve opening.

$$f(x) = x \quad (3)$$

The quick-opening characteristic is given by Eq. (4); it responds quickly at small openings and saturates at large openings.

$$f(x) = 1 - e^{-(4x)} \quad (4)$$

The equal-percentage characteristic is given by Eq. (5); for a given opening increment, the percentage change in flow remains approximately constant.

$$f(x) = 30^{x-1} \quad (5)$$

In this study, V1 and V3 use equal-percentage characteristics, while V2 and V4 use linear characteristics. The three characteristic curves are compared in Fig. 3.

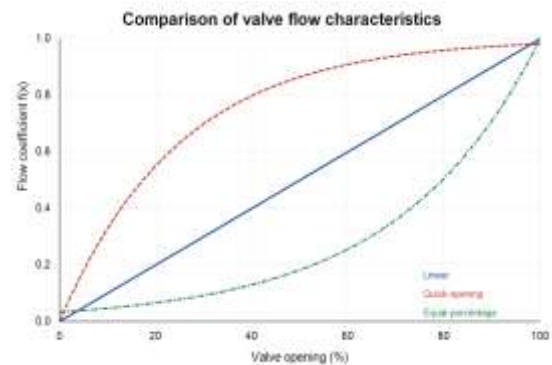


Figure 3 Comparison of valve flow characteristics

At small openings, the equal-percentage curve is the flattest and the quick-opening curve is the steepest; this difference

provides a basis for valve adjustment under different operating conditions.

3.3 Pipeline Pressure-Flow Coupling Solution

The four valves are connected in series and parallel, so the node pressures and branch flows are coupled. A change in any valve opening redistributes the pressure and flow throughout the network, requiring a system-level solution. According to Fig. 2, six unknowns are defined: p_{sys} , p_{gin} , p_{gout} , $\dot{m}_{total}$, $\dot{m}_{bypass}$, and $\dot{m}_{gen}$, as expressed in Eq. (6).

$$X = [p_{sys}, p_{gin}, p_{gout}, \dot{m}_{total}, \dot{m}_{bypass}, \dot{m}_{gen}]^T \quad (6)$$

The variables satisfy the flow, mass-conservation, and pressure-drop equations given by Eqs. (7)-(12).

$$\dot{m}_{total} = Cv1 \times 1 \sqrt{(P_{source} - p_{sys})} \quad (7)$$

$$\dot{m}_{bypass} = Cv2 \times 2 \sqrt{(p_{sys} - P_{down})} \quad (8)$$

$$\dot{m}_{total} = \dot{m}_{bypass} + \dot{m}_{gen} \quad (9)$$

$$\dot{m}_{gen} = Cv3 \times 3 \sqrt{(p_{sys} - p_{gin})} \quad (10)$$

$$\dot{m}_{gen} = Cv4 \times 4 \sqrt{(p_{gout} - P_{down})} \quad (11)$$

$$p_{gin} - p_{gout} = K_{turb} \dot{m}_{gen}^2 \quad (12)$$

In these equations, P_{source} and P_{down} are the source and downstream pressures, $Cv1$ - $Cv4$ are the valve flow coefficients, and K_{turb} is the turbine flow resistance. The total impedance of the generation branch is defined by Eq. (13).

$$Z_{gen} = 1/(Cv3 \times 3)^2 + K_{turb} + 1/(Cv4 \times 4)^2 \quad (13)$$

Eqs. (14) and (15) can be obtained from Eq. (13).

$$\dot{m}_{gen} = \sqrt{[(p_{sys} - P_{down})/Z_{gen}]} \quad (14)$$

$$\dot{m}_{bypass} = Cv2 \times 2 \sqrt{(p_{sys} - P_{down})} \quad (15)$$

Combining Eqs. (9), (14), and (15) yields Eq. (16).

$$Cv1 \sqrt{(P_{source} - p_{sys})} = Cv2 \times 2 \sqrt{(p_{sys} - P_{down})} + \sqrt{[(p_{sys} - P_{down})/Z_{gen}]} \quad (16)$$

Eq. (16) is solved by direct substitution iteration, and the variables are back-substituted after convergence.

3.4 Turbine Work and Equipment State Model

After obtaining $\dot{m}_{gen}$, p_{gin} , and p_{gout} , the turbine work, power generation, speed, temperature, and vibration are calculated.

The turbine expansion is approximated as an adiabatic process. The ideal isentropic outlet temperature is given by Eq. (17), with $k = 1.31$.

$$T2s = T1 (p_{gout}/p_{gin})^{((k-1)/k)} \quad (17)$$

Considering friction and leakage losses, the isentropic efficiency η_{turb} is introduced, and the actual outlet temperature is given by Eq. (18).

$$T2 = T1 - \eta_{turb} (T1 - T2s) \quad (18)$$

In this study, $\eta_{turb} = 0.85$.

3.4.1 Power Generation

The work done by unit mass of gas is the specific enthalpy drop, as expressed in Eq. (19).

$$\Delta h = cp (T1 - T2) \quad (19)$$

With $cp = 2.2 \text{ kJ/(kg}\cdot\text{K)}$, substituting Eq. (18) into Eq. (19) yields Eq. (20).

$$\Delta h = cp \eta_{turb} T1 [1 - (p_{gout}/p_{gin})^{((k-1)/k)}] \quad (20)$$

The turbine shaft work is the product of the specific enthalpy drop and mass flow rate, as given by Eq. (21).

$$W_{turb} = \dot{m}_{gen} \Delta h \quad (21)$$

Considering the generator efficiency η_{gen} , the actual power generation is given by Eq. (22).

$$Pe = \dot{m}_{gen} cp \eta_{turb} \eta_{gen} T1 \times [1 - (p_{gout}/p_{gin})^{((k-1)/k)}] \quad (22)$$

Here, $\eta_{gen} = 0.97$, accounting for copper loss, iron loss, and mechanical friction. Eq. (22) shows that power generation is approximately proportional to the mass flow rate and follows a power-law relationship with the expansion ratio, while increasing with the turbine and generator efficiencies.

3.4.2 Generator Temperature Rise Model

Generator losses generate heat and increase the body temperature. A simplified steady-state temperature-rise model is used to estimate the generator temperature, as given by Eq. (23).

$$T_{gen} = T_{amb} + Pe K_{thermal} \quad (23)$$

Here, $T_{amb} = 25 \text{ }^\circ\text{C}$ and $K_{thermal} = 0.13 \text{ }^\circ\text{C/kW}$.

3.4.3 Bearing Vibration Model

Bearing vibration is an important indicator of rotating-machinery health. The vibration is simplified as the superposition of base vibration, centrifugal vibration, and flow-induced vibration, as given by Eq. (24).

$$v = v0 + \alpha(n/N_{sync})^2 + \beta \dot{m}_{gen} \quad (24)$$

Here, $v0 = 1.5 \text{ mm/s}$, $\alpha = 3.0 \text{ mm/s}$, and $\beta = 0.45 \text{ mm}\cdot\text{s}^{-1}/(\text{kg}\cdot\text{s}^{-1})$. The model describes the vibration trend under different operating conditions and provides a basis for fault injection and alarm design.

4. 3D Visualization and Interactive Design

A digital twin platform must not only calculate operating parameters but also present equipment status, pipeline flow, and abnormal conditions intuitively. This chapter introduces the 3D modeling workflow and multimodal interaction design.

4.1 3D Modeling Workflow of the Digital Twin System

Based on design drawings and field photographs, models of pipelines, valves, the turbine expander, generator, and instruments are built in Blender. To meet Web loading and interaction requirements, non-essential components are simplified, and the model is assembled according to the actual pipeline topology, with transformation constraints defined for moving parts. The model is exported in glTF 2.0 format and loaded with Three.js; the scene, camera, and renderer are configured for browser-based 3D visualization. The modeling workflow is shown in Fig. 4.

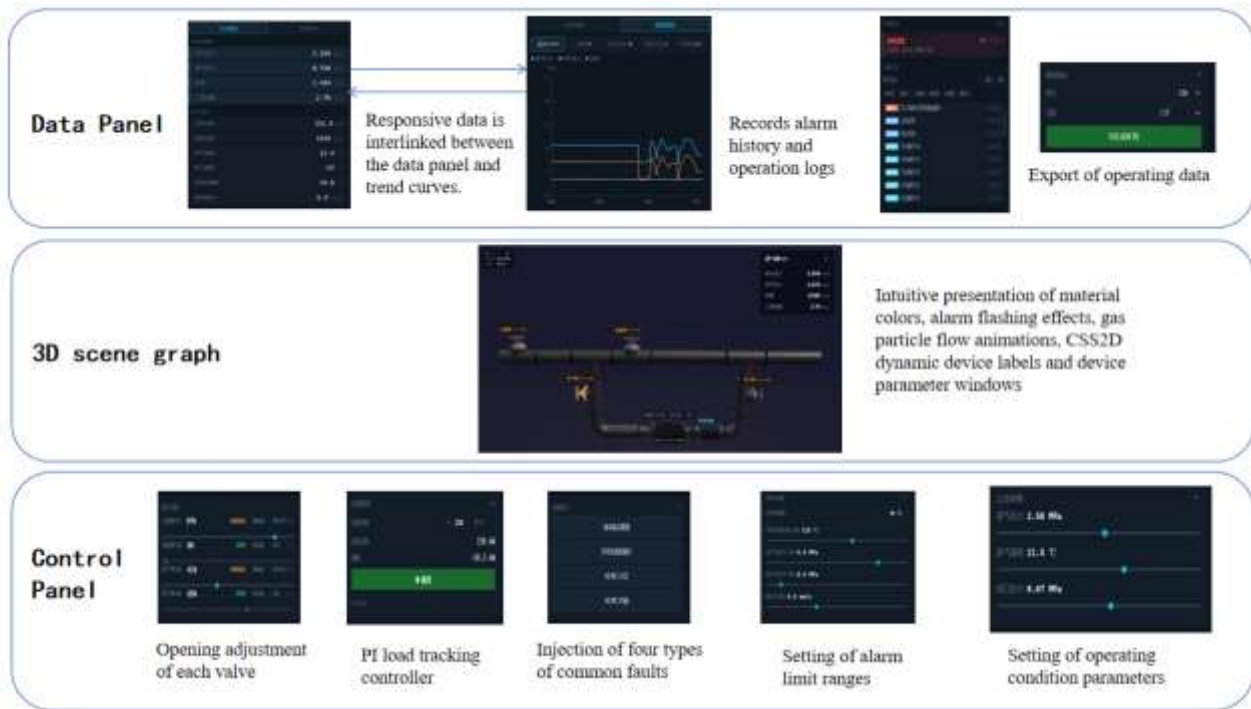


Figure 4 Blender-based 3D modeling workflow

4.2 Multimodal Interaction

The platform consists of a data panel, a 3D scene, and a control panel, which are linked through Pinia. The data panel displays 15 parameters, including pressure, flow rate, power, speed, and temperature, and provides alarm history and CSV export. The 3D scene presents equipment status, gas-particle

flow, and alarm flashing. The control panel provides valve openings, PI target power, fault injection, and threshold settings. Operator commands drive the simulation, and the results are fed back to the interface, as shown in Fig. 5.

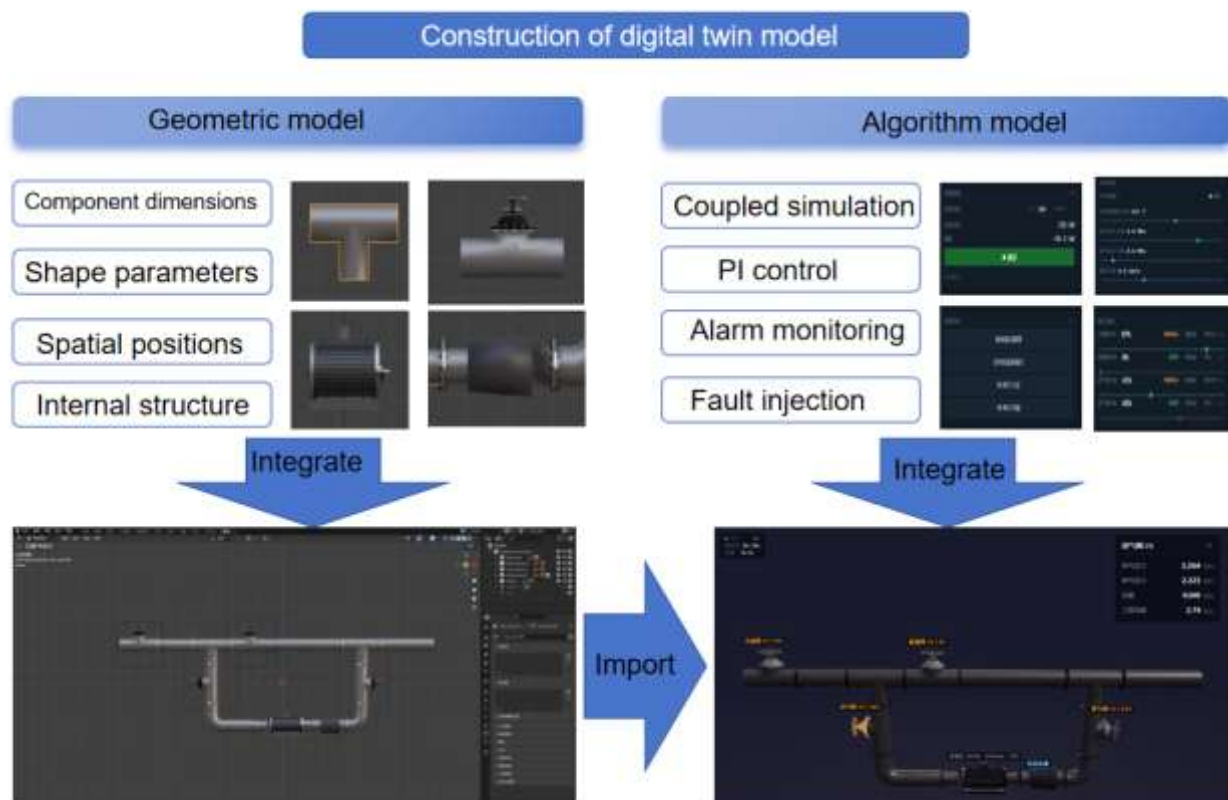


Figure 5 Functional diagram of the digital twin platform

5. Operation Control Function Design

This chapter designs three modules: automatic load tracking, fault injection, and alarm management, forming a control loop from target setting to abnormal-response handling.

5.1 PI Automatic Load Tracking Control

Variations in downstream gas demand cause power fluctuations. PI control is used to automatically adjust valve openings so that the actual power tracks the target value.

5.1.1 Control Strategy

The input to the PI controller is the error between the target power P_{ref} and the actual power P_e , as given by Eq. (25).

$$e(k) = P_{ref} - P_e(k) \quad (25)$$

An incremental PI algorithm is used, and the valve-opening increment is given by Eq. (26).

$$\Delta u(k) = K_p[e(k) - e(k-1)] + K_i e(k) \quad (26)$$

Here, K_p and K_i are the proportional and integral gains, respectively. The proportional term improves the response speed, while the integral term eliminates steady-state error, jointly balancing tracking accuracy and stability.

5.1.2 Dual-Valve Coordination

The controller output acts on both V3 and V1 to achieve dual-valve coordination, as given by Eqs. (27) and (28).

$$x3(k) = x3(k-1) + \Delta u(k) \quad (27)$$

$$x1(k) = x1(k-1) + 0.7 \Delta u(k) \quad (28)$$

The V1 coordination coefficient is 0.7, meaning that the adjustment of the main valve is 70% of that of the inlet valve. When the load increases, V1 increases the total inlet flow and V3 increases the flow split to the generation branch, while the smaller V1 adjustment avoids excessive pressure fluctuations.

5.2 Fault Injection and Simulation

Fault injection is an important means of validating control strategies and alarm mechanisms. Four fault types are considered: bearing vibration surge (wear or poor lubrication), generator temperature rise (cooling failure), V3 sticking (actuator jam), and V2 internal leakage (seal failure). Virtual reproduction of these faults allows system responses and alarm logic to be evaluated.

5.3 Alarm System Design

5.3.1 Alarm Threshold Monitoring

The alarm system monitors generator temperature, bearing vibration, inlet pressure, and outlet pressure, with thresholds listed in Table 1. Upper limits are used for temperature, vibration, and inlet pressure, while a lower limit is used for outlet pressure. Thresholds can be adjusted in real time through the control panel.

Table 1 Monitoring parameters

No.	Parameter	Alarm condition	Default threshold	Adjustable range	Unit
1	Generator temperature T_{gen}	$T_{gen} > T_{limit}$	115	60-150	°C
2	Bearing vibration v	$v > V_{limit}$	6.5	2-15	mm/s
3	Inlet pressure p_{gin}	$p_{gin} > P_{high}$	4.5	2.5-5.0	MPa
4	Outlet pressure p_{gout}	$p_{gout} < P_{low}$	0.4	0.3-1.5	MPa

Threshold checks are performed in each simulation cycle. When a parameter exceeds its threshold, the system is marked as alarmed and a history record is generated; simultaneous violations are recorded separately.

5.3.2 Alarm Cooldown and History Management

To avoid repeated alarms, a 30 s cooldown is used. The new-alarm condition is given by Eq. (29).

$$A_p = (P_i \notin [P_{i,low}, P_{i,high}]) \wedge [(t - \tau_p) > T_{cool}] \quad (29)$$

Here, P_i is the current measured value, $P_{i,low}$ and $P_{i,high}$ are the lower and upper thresholds, and $T_{cool} = 30$ s. A new alarm is recorded only when the parameter is out of range and more than 30 s have elapsed since the previous alarm.

Alarm history records the alarm ID, trigger time, parameter name, measured value, and threshold, and is stored in Pinia. A new record is generated only after the cooldown period when the same parameter exceeds its threshold again.

6. System Testing and Results Analysis

The test environment was Windows 11 Professional, an Intel Core i7-14650HX processor, 32 GB RAM, an NVIDIA GeForce RTX 4060 GPU, and the Edge 151 browser.

6.1 Simulation Model Validation

Four conditions were set: baseline, high pressure difference, low pressure difference, and bypass open. Inlet pressure, outlet pressure, pressure difference, V2 opening, and power generation were observed, as listed in Table 2.

Table 2 Comparison of operating conditions

Condition	Inlet pressure (MPa)	Outlet pressure (MPa)	Pressure difference (MPa)	V2 opening (%)	Power (kW)	Verification
Baseline	2.50	0.67	1.83	0	350	Consistent
High pressure difference	3.00	0.67	2.33	0	420	Reasonable
Low pressure difference	1.50	0.67	0.83	0	120	Reasonable
Bypass open	2.50	0.67	1.83	50	263	Reasonable

As shown in Table 2, increasing the pressure difference raised the power from 120 to 420 kW. When V2 was opened, part of

the gas bypassed the generation branch, reducing the power from 350 to 263 kW. The trends under the four conditions agree

with the differential pressure power generation characteristics, indicating that the model captures the main physical behavior.

6.2 PI Control Performance Test

Under normal operation, the power was 350 kW. The PI target was set to 300 kW and tracking was started; the result is shown in Fig. 6.

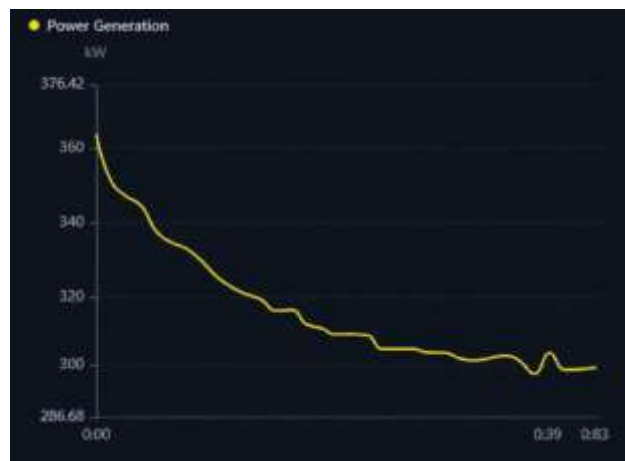


Figure 6 Power generation trend

The power decreased from 350 kW and reached about 300 kW after approximately 30 s, with small fluctuations around the target. The transition was smooth without abnormal jumps, indicating that the PI controller converged to within $\pm 5\%$ of the target within 30 s.

6.3 Fault Injection Test and Result Analysis

Under the baseline condition, the four faults were injected using the default thresholds in Table 1, and the alarms, system states, and recovery processes were recorded.

Bearing vibration fault: the normal vibration was about 5.8 mm/s. After injection, it rose to 12.0 mm/s within 3 s, exceeding the 6.5 mm/s threshold and triggering sound, 3D flashing, and history records. No repeated alarm occurred during the cooldown period, and the vibration returned to normal after the fault was cleared.

Generator temperature fault: the normal temperature was about 70 °C. After injection, it rose to 155 °C within 3 s, exceeding the 115 °C threshold and triggering the alarm. No repeated alarm occurred during the cooldown period, and the temperature recovered after the fault was cleared.

V3 sticking fault: during automatic tracking, the V3 opening was locked and the PI controller could not adjust it, so the power could not track the target. This indicates that actuator sticking breaks the control loop and requires manual intervention.

V2 internal leakage fault: V2 was fully closed under normal conditions. After injection, the bypass path opened to an equivalent 15% within 10 s, while the V2 reading remained 0%; the bypass flow increased to about 1.0 kg/s, approximately one-third of the rated generator flow. The leakage reduced the system pressure, generation-branch flow, generator temperature, and vibration. Because no parameter exceeded its threshold, the fault could only be identified from the flow and power trends.

All four faults produced corresponding responses. The vibration and temperature faults triggered the three-level alarm linkage, and the 30 s cooldown reduced repeated alarms. V3 sticking

appeared as tracking failure, while V2 leakage appeared as a trend anomaly, providing a basis for adding control-deviation and leakage-residual detection.

7. Conclusion

This paper developed a four-layer digital twin simulation platform for differential pressure power generation. A four-valve pipeline coupling model was established with linear, quick-opening, and equal-percentage flow characteristics. Flow, mass-conservation, and turbine pressure-drop equations were solved to calculate pressure, flow, power, temperature rise, and vibration. A Web-based 3D scene was built with Blender and Three.js; incremental PI load tracking, four fault-injection scenarios, and configurable thresholds were designed to form an injection-detection-alarm-handling-recovery verification framework.

Simulation results showed that valve adjustment changed pressure, flow, and power; the four operating conditions agreed with differential pressure power generation behavior; the PI controller converged to within $\pm 5\%$ of the target within 30 s; and all four faults produced corresponding responses.

This study has limitations. The platform is driven by model-generated data and has not yet been connected to field SCADA or sensor data. The pipeline model uses a quasi-steady-state assumption, and the turbine, temperature-rise, and vibration models are simplified, with some coefficients based on engineering experience. Fault injection mainly verifies alarm and handling procedures, and transient thermal inertia is not fully represented. Future work will integrate measured data for parameter calibration, add dynamic thermal processes and model-based detection of valve sticking and internal leakage, and expand the operating-condition coverage.

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9. References

- [1] Huang H, Liu M M, Wang J L. Positioning and policy suggestions of China's natural gas development under the dual-carbon goal[J]. City Gas, 2023(6):29-34.
- [2] Liu K, Jiang F H, Zhang X S, et al. Research on the development path of green and low-carbon methanol based on China's national conditions[J/OL]. Strategic Study of CAE, 1-16[2026-06-01]. <https://link.cnki.net/urlid/11.4421.G3.20260529.1622.006>.
- [3] Gao N, Li J X, Zhang J W, et al. Application prospects of differential pressure power generation technology in long-distance natural gas pipelines[J]. Petroleum & Petrochemical Energy Conservation and Measurement, 2025, 15(8):7-11.
- [4] Yang Z Q, Ma J G, Yun Q, et al. Current status and development trends of natural gas differential pressure power generation technology[J]. Oil & Gas and New Energy, 2025, 37(5):131-136.

- [5] Prokhorova V, Budanov M, Brovko K, et al. Construction of a digital twin model for a system that monitors the technical condition of a nuclear power plant power unit[J]. *Eastern-European Journal of Enterprise Technologies*, 2026, 2(9(140)):64-71. DOI:10.15587/1729-4061.2026.356915.
- [6] Wang D, Liu Q, Yang J, et al. Digital twin for power equipment: lifecycle framework, enabling technologies, and prospects in next-generation power systems[J]. *Computing*, 2026, 108(4):62. DOI:10.1007/S00607-026-01650-Z.
- [7] Malik T M, Obaid M H, Rasool F H. Integrating digital twin and sensor technologies for future-ready smart grids[J]. *Discover Electronics*, 2026, 3(1):42. DOI:10.1007/S44291-026-00196-W.
- [8] Xilong Z, Huang H, Zhu X, et al. Digital twin-driven subdomain adaptive fault diagnosis method for imbalanced data in rolling bearings[J]. *Engineering Research Express*, 2026, 8(8):085208. DOI:10.1088/2631-8695/AE5C60.
- [9] Jiang X M, Meng J G, Hui H Y, et al. Health intelligent monitoring of multistage centrifugal compressors based on data-model fusion digital twin[J/OL]. *Journal of System Simulation*, 1-13[2026-06-01]. <https://doi.org/10.16182/j.issn1004731x.joss.25-1072>.
- [10] Fang Y N, He R C. Adaptive optimization of gasoline blending for intelligent refineries: five-dimensional digital twin system and dynamic closed-loop control[J/OL]. *Journal of System Simulation*, 1-19[2026-06-01]. <https://doi.org/10.16182/j.issn1004731x.joss.26-0102>.
- [11] Xie X H, He J L, Xu N, et al. Research and application of digital twin-driven intelligent integrity management of oil and gas pipelines[J]. *Petrochemical Automation*, 2026, 62(2):6-12. DOI:10.26992/j.cnki.issn1007-7324.2025.09.233.
- [12] An P F. Research on integrity management of natural gas pipelines based on digital twin technology[J]. *Chemical Management*, 2025(22):93-96. DOI:10.19900/j.cnki.ISSN1008-4800.2025.22.025.
- [13] Sun H W. Research on operation condition detection of hydro-generator units based on digital twin technology[J]. *Electric Engineering*, 2025(24):289-291. DOI:10.19768/j.cnki.dgjs.2025.24.087.
- [14] Li Q, He Y, Geng X, et al. Digital twin-driven condition monitoring methods for power electronic devices: Application and challenges[J]. *Renewable and Sustainable Energy Reviews*, 2026, 235:116983. DOI:10.1016/J.RSER.2026.116983.
- [15] Chen Y N, Wen X, Zhu X P, et al. Construction of a digital twin system for pipeline leak detection in gas surface stations[J]. *Chemical Engineering of Oil & Gas*, 2026, 55(2):166-174.