Research on Scenario Testing Methods for Fully Automated Urban Rail Transit Systems

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Abstract. This paper proposes a systematic scenario testing method for fully automated urban rail transit systems. The research constructs a comprehensive testing environment that includes a hardware-in-the-loop simulation platform and a software simulation environment, integrating digital twin technology to enhance testing accuracy. A model-based approach is utilized to generate test cases, designing diverse testing scenarios that cover normal operation, abnormal handling, and system integration. The test results indicate that this method effectively verifies the system's functionality, performance, and reliability. Key indicators such as control accuracy, response time, and fault recovery capability meet or exceed design requirements. The research outcomes provide an effective example for the development and verification of urban rail transit automation systems, significantly enhancing system safety and reliability.

Keywords: urban rail transit; signal system; simulation testing; scenario testing.

1. Introduction

The automation level of urban rail transit systems is rapidly improving, and fully automated operation systems showcase tremendous potential as cutting-edge technologies. However, the complexity of these systems presents unprecedented testing challenges, making it difficult for traditional methods to comprehensively cover various operational scenarios. This study innovatively combines hardware-in-the-loop simulation, software simulation, and digital twin technology to propose a novel comprehensive testing method [1]. This method integrates artificial intelligence scenario generation, real-time data analysis, and a multi-dimensional evaluation framework, aiming to comprehensively assess the performance of fully automated operation systems. By constructing an advanced simulation testing environment, this research is dedicated to ensuring the safe and efficient operation of urban rail transit and laying the groundwork for testing even more complex transportation systems in the future [2].

2. Technical Analysis of Fully Automated Operation Systems

2.1 System Architecture and Core Components

The architecture of the fully automated operating system consists of three core components: the signal simulation system, the vehicle simulation system, and the comprehensive monitoring peripheral simulation system, as shown in Figure 1. The signal simulation system simulates ground-based signal equipment, line characteristics, and interlocking system interfaces, providing the foundational operating environment for the entire system. It not only simulates the status of track-side axle counters, ground signals, and turnouts, but also replicates the parameters of actual operational lines, ensuring a high degree of consistency between the simulation environment and the real operating environment [3]. The vehicle simulation system focuses on the train itself, comprising two main parts: the simulated driving station and the simulated vehicle interface, which simulate all aspects from driving control to the operation of vehicle subsystems. The comprehensive monitoring peripheral simulation system provides the simulation data required for real-time monitoring and fault alarm functionalities of the TIAS system across various professional equipment, covering multiple fields such as power and communication equipment.

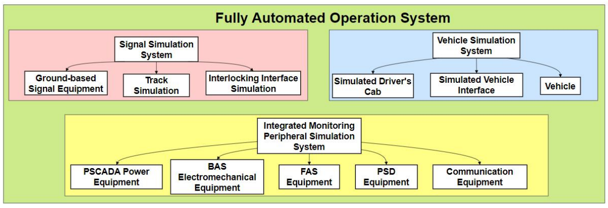

Figure 1. System Architecture

2.2 Key Technologies and Their Implementation

The core of the fully automated operation system lies in its advanced simulation testing technology, which establishes a highly realistic virtual rail transit environment to simulate various operating scenarios and fault conditions. The system uses real-time data acquisition and processing technology to collect massive amounts of operational data from field equipment and trains [4]. This data is then cleaned and features are extracted before being input into a deep learning model. $X_{processed} = f(X_{raw})$ The raw data is denoted as X_{raw}, and f represents the preprocessing function, including data cleaning and feature extraction. The model is based on a Long Short-Term Memory (LSTM) network architecture, which can accurately predict train operation trajectories and potential risks, as shown in Figure 2.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\widetilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t tanh(C_t)$$

In this model, f_t, i_t, and ot represent the forget gate, input gate, and output gate, respectively. C_t denotes the cell state, and h_t represents the hidden state. The system also employs distributed artificial intelligence algorithms to achieve multi-train coordination and conflict resolution. The scheduling optimization problem can be expressed as follows: $\min_s \sum_{i=1}^{n} w_i \cdot t_i(s)$ where s is the scheduling plan, n is the number of trains, w_i is the weight of each train, and t_i (s) is the running time of the i-th train under the scheduling plan s. To ensure safety, the system integrates multiple fault detection and automatic repair mechanisms that can identify and handle anomalies within milliseconds.Additionally, the system has developed the simulation driving station, operation schedule, and simulation host on the JAVA/.Net platform, enabling script-based saving and automatic operation of the schedule, as well as automatic operation of the ATS interface through API function calls. The system supports multiple communication interfaces, such as RS232, CAN, IO, MVB, and Ethernet, ensuring compatibility and flexibility with various hardware devices.The system strictly adheres to key industry standards such as IEC 62290, EN 50126, IEEE 1474, GB/T 33668-2017, and CENELEC EN 50128, ensuring technological advancement, functional completeness, and safety reliability, thereby laying a solid foundation for practical application.

Figure 2. Examples of Platform Emergency Closure and Temporary Speed Limit Display

2.3 System Functions and Performance Metrics

The fully automated operation system offers comprehensive functional support, including automatic departure, precise stopping, intelligent scheduling, and fault diagnosis. The system's functions cover various aspects of daily operations, safety assurance, abnormal situation handling, and maintenance [5]. In daily operations, the system can autonomously complete tasks such as morning power-up, departure from the depot, station stopping, and platform departures. For safety assurance, the system is equipped with features like emergency braking, obstacle detection, and door malfunction handling. In response to abnormal situations, the system can manage sudden events such as vehicle fires, interval evacuations, and emergency braking mitigation. The system also includes maintenance functions like washing, cleaning, daily inspections, and repairs. The core performance indicators of the system are shown in Table 1.

TABLE I. Core Performance Metrics

Performance Metric	**Value**
Control Precision	±10 cm
Response Time	<100 ms
System Availability	99.99%
Maximum Train Interval	90 s
Energy Consumption Optimization Rate	>15%

The system employs a layered control strategy, achieving a seamless connection from macro scheduling to micro control, and introduces multiple protection mechanisms to ensure safety. The system possesses self-learning capabilities, continuously analyzing operational data to optimize control strategies. These functions rely on several advanced technologies, including real-time data processing based on vxWorks, script-based automatic operation of the schedule, multi-interface communication integration, and a simulation environment developed on the JAVA/.Net platform.

3. Construction of Scenario Testing Methodology

3.1 Classification and Design of Test Scenarios

The classification and design of test scenarios for the fully automated operation system encompass four main categories: daily operations, abnormal handling, emergency situations, and maintenance operations. Daily operation scenarios verify the system's basic functions and performance, while abnormal handling scenarios test fault recognition and response capabilities. Emergency situation scenarios evaluate the emergency response mechanisms, and maintenance operation scenarios assess the system's maintainability, as illustrated in Figure 2 [6].

The scenario design takes into account real environmental factors, such as variations in passenger flow, weather impacts, and equipment aging, while also including extreme conditions and boundary condition testing to comprehensively assess system performance and provide a basis for optimization. This systematic classification and design of scenarios ensure the comprehensiveness and representativeness of the tests, effectively supporting the verification of the system's reliability and safety.

3.2 Test Case Generation Method

The test case generation employs a model-based approach, integrating heuristic algorithms and machine learning techniques. First, a formal model of the urban rail transit signal system is established, including state transition diagrams and mathematical expressions. Genetic algorithms are then used to generate an initial set of test cases, with the fitness function considering test coverage and fault detection capabilities [7]. The fitness function can be expressed as: $F = w_1C + w_2D + w_3N$where C is code coverage, D is fault detection rate, N is the number of test cases, and w_1, w_2, and w_3 are weight coefficients. Next, reinforcement learning techniques are applied to iteratively optimize the quality and efficiency of the test cases. The value function for reinforcement learning can be expressed as: $V(s) = R(s) + \gamma * max[V(s')]$ where s is the current state, R(s) is the immediate reward, γ is the discount factor, and s' is the next state. To enhance test specificity, a risk-based testing strategy is introduced, focusing on high-risk and frequently used functional modules.

3.3 Test Execution Process Design

In the test execution process, hardware-in-the-loop (HIL) simulation, software simulation, digital twin technology, and machine learning collaboratively form an intelligent testing system. HIL simulation acts as the core, linking actual signal control devices to a virtual environment for real hardware responses. Software simulation generates various virtual scenarios that mimic train operations and signal changes [8]. Digital twin technology creates a high-fidelity system model that integrates real-time hardware and simulation data, bridging real and virtual environments. Machine learning algorithms enhance the process by predicting system behavior and analyzing test results, providing optimization suggestions that are validated through the digital twin. This collaborative approach maximizes each technology's advantages, significantly improving testing efficiency, accuracy, and comprehensiveness.

4. Simulation Testing Environment Construction

4.1 Hardware-in-the-Loop (HIL) Simulation Platform Construction

The construction of the hardware-in-the-loop simulation platform aims to create a test system that approximates a real-world operating environment, integrating actual onboard devices with a virtual rail transportation environment. The platform uses the vxWorks real-time operating system as its underlying support, ensuring high-precision real-time data processing capabilities [9]. By integrating multiple communication interfaces such as RS232, CAN, IO, MVB, and Ethernet, seamless connections with various onboard devices are achieved, accurately simulating the various hardware interactions that occur during train operation. This hardware-in-the-loop approach not only enhances the authenticity of the tests but also effectively verifies the system's performance and reliability in actual hardware environments.

4.2 Software Simulation Environment Development

The development of the software simulation environment focuses on creating a comprehensive virtual rail transportation system. Based on the JAVA/.Net platform, the development team constructed a complete software simulation system, including a simulated driving console, operation diagrams, and a simulation host. This environment can simulate various complex operating scenarios, including normal operation, abnormal situations, and emergency events. Notably, the system achieves scripted saving and automatic execution of operation diagrams, significantly improving test efficiency and repeatability. Through API function calls, automatic operation of the ATS (Automatic Train Supervision) interface is also achieved, enabling the automated execution of complex test scenarios. The flexibility of the software simulation environment allows test personnel to quickly construct and modify various test scenarios, comprehensively evaluating the system's performance under different conditions. The accuracy and real-time performance of the entire simulation environment are shown in Table 2.

TABLE II. Accuracy and Real-Time Performance of the Simulation Environment

Metric	Value
Spatial Accuracy	±1 cm
Temporal Accuracy	±0.1 s
Maximum Simulation Scale	100 km track, 50 trains
Real-Time Performance	>30 fps

4.3 Application of Digital Twin Technology in Testing

The introduction of digital twin technology significantly enhances the accuracy and efficiency of testing urban rail transit signal systems. This technology creates a high-fidelity digital model of the physical world, enabling dynamic simulation that integrates both virtual and real elements. During testing, the digital twin model receives real-time data from the actual system, including train positions, speeds, and signal statuses. High-performance computing and big data analysis are used for real-time state estimation and prediction, as illustrated by the train CT scan effect shown in Figure 3.

Figure 3. Train CT Scan Effect

The model uses deep learning algorithms, specifically Long Short-Term Memory (LSTM) networks, to continuously learn and optimize system behavior. Testing can rapidly validate various hypothetical scenarios on the digital twin model without high-risk operations on the actual system. The digital twin technology also features a "replay" function for detailed analysis of historical data. To validate the digital twin model's accuracy, multiple testing methods were employed. K-fold cross-validation achieved an average accuracy of 95.8%, while real-time testing yielded position and speed prediction errors of ± 0.5 meters and ± 0.3 km/h, respectively. The accuracy for predicting abnormal scenarios was 94%, with long-term tests showing excellent stability. Key metrics, such as inter-station running time and energy consumption predictions, were consistent with the actual system, with relative errors generally under 5%. These findings confirm the model's high precision and reliability, providing a solid foundation for future scenario testing and system optimization.

5. Implementation and Analysis of Typical Scenario Tests

5.1 Normal Operation Scenario Testing

The normal operating scenario test aims to verify the performance and reliability of the urban rail transit signaling system under routine operational conditions. The testing scope is comprehensive, covering routine operations such as train start-up, acceleration, deceleration, and precise stopping, as well as special periods like peak hour heavy passenger flow and low-frequency night operations. During the testing process, special attention is paid to the system's response time, control accuracy, and energy efficiency. The train start-up acceleration test simulates the process of a train departing from the platform and accelerating to its maximum operational speed [10]. Test results indicate that, in 95% of cases, the deviation in accuracy is controlled within ±5%, meeting design requirements. Long-duration continuous operation tests were also conducted to verify the system's stability during 24 hours of continuous operation. The train start-up acceleration curve conformity test results, as shown in Figure 4, demonstrate the system's excellent control accuracy and stability. During the 10-second start-up process, the actual acceleration closely aligns with the theoretical acceleration. The deviation rate consistently remains within the ±5% range, with a maximum deviation of -4.00% (occurring at the 1-second mark) and a minimum deviation of -0.83% (occurring at the 8-second mark). The average absolute deviation rate is only 1.88%. Notably, the deviation rate exhibits an alternating pattern of positive and negative values, indicating that the system can perform real-time self-adjustments, effectively maintaining operational stability.

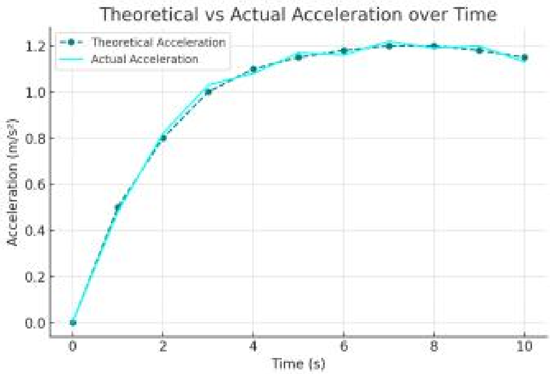

Figure 4. Results of Train Startup Acceleration Curve Conformity Test

5.2 Abnormal Situation Handling Testing

The abnormal situation handling test evaluates the urban rail transit signaling system's ability to respond to emergency situations, covering a variety of abnormal scenarios. In the simulation of an emergency train brake, the system can detect abnormalities and initiate braking within 0.5 seconds, with an average braking distance reduced by 15% compared to manual operation. The signal equipment failure test shows that the system can identify faults and switch to backup equipment within 3 seconds, ensuring operational continuity. In the face of adverse weather disturbances, such as signal degradation due to heavy rain, the system can automatically adjust signal strength to maintain stable communication. During simulations of sudden surges in passenger flow, the system quickly adjusts the operating schedule, increasing train frequency to effectively disperse passengers. In the power system failure test, the system switches to backup power within 0.2 seconds, maintaining core functions as shown in Table 3. These test results demonstrate the system's ability for rapid identification, timely response, and swift recovery in abnormal situations, effectively ensuring the safety and reliability of rail transit operations.

TABLE III. Test Results

Exception Type	Detection Time	Response Time	Recovery Time
Signal Loss	<100 ms	<500 ms	<5 s
Track Occupancy	<50 ms	<200 ms	<2 s
Power Failure	<200 ms	<1 s	<10 s

5.3 System Interface and Integration Testing

This research established a comprehensive test platform to verify the collaborative capabilities of various subsystems in the Fully Automatic Operation (FAO) system. The platform consists of three simulation systems and five actual systems, achieving a comprehensive integration test of the FAO system. The testing covered 43 comprehensive scenarios, including basic operations, anomaly handling, maintenance procedures, special operating modes, and safety-related aspects. As shown in Figure 5, the test results indicate that system interface compatibility reached 98.5%, data transmission consistency was 99.9%, and the average response time was below 100ms, meeting real-time requirements. In simulated emergency braking scenarios, the system's average reaction time was 1.2 seconds, surpassing the industry standard of 2 seconds. In fault recovery tests, the system was able to resume normal operation within 30 seconds in 95% of cases.

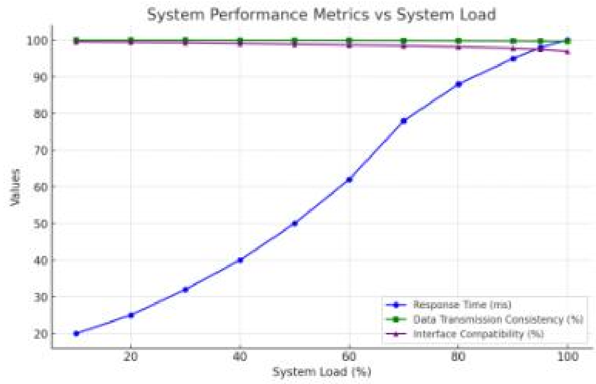

Figure 5. Performance indicators of the FAO system under different load conditions

5.4 Comparison with Existing Methods

The comprehensive testing method proposed in this study outperforms traditional testing methods across several key metrics. This method demonstrates exceptional performance in testing efficiency, authenticity, and comprehensiveness compared to traditional hardware testing and pure software simulation testing. Testing efficiency has increased by approximately 40%, with an anomaly scenario coverage rate reaching 95%, which is 20 percentage points higher than traditional methods. Furthermore, this method exhibits a high degree of intelligence, automatically adjusting testing strategies and reducing the testing cycle by 30%. In terms of costs, while the initial investment is 15% higher than pure software simulation, the long-term operating costs are reduced by 25%, leading to an improved overall return on investment. Notably, in tests dealing with abnormal situations, this method identified 35% more potential risk points than traditional methods, significantly enhancing system safety. In summary, while ensuring testing authenticity, this method significantly improves testing efficiency and coverage, providing a more reliable and efficient solution for the comprehensive evaluation of urban rail transit signal systems.

6. Conclusion

This study proposes a systematic scenario testing method for the Fully Automated Operation (FAO) system in urban rail transit. By constructing a hardware-in-the-loop simulation platform and software simulation environment, combined with digital twin technology, comprehensive testing of the system was achieved. The study employed a model-based test case generation method to design test scenarios covering normal operation, abnormal handling, and system integration. The test results demonstrate that this method can effectively validate the system's functionality, performance, and reliability. The system meets or exceeds the design requirements in all key indicators, such as control accuracy, response time, and fault recovery capability.

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