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Research on Dynamic Health Assessment of Metro Integrated Supervision and Control System Equipment Based on Digital Twin

Yuanchen Liu, Changchun Liu*, Jianmin Xu, Jiaqiang Ji

Shenyang Siasun Robot & Automation Co., Ltd., Shenyang, Liaoning, China
**Corresponding Author*

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Abstract: On account of the diverse types and complex operating environments of the metro ISCS equipment, the traditional threshold alarm and the periodic maintenance is not enough to characterize the health of the equipment in an accurate way. In this paper, digital twin technology is introduced, the "data-driven- model mapping- dynamic assessment- early warning intervention" four-layer framework is constructed, the comprehensive health index model which takes the operation deviation, the cumulate degradation and the environment into account is proposed, and the LSTM is used for trend prediction. Validation on the metro Line 3 gives the assessment accuracy of 92.6%, which is 17.3 percentage points higher than the traditional way, and the average early warning lead time is extended to 7.8 days. The countermeasures for data governance, model updating and the personnel training are given in practical.

1. Introduction

With surging equipment volume and mounting maintenance pressure, the urban rail transit has entered a networked operation phase[1]. The metro ISCS integrated with power, environment control, fire protection and security subsystems, whose health will affect the safety of the train. For most of the lines, the maintenance way is still periodic maintenance plus post failure repair[2]. The way will suffer more over maintenance, under maintenance, high failure, and not using the data well. With the digital twin technology which is to construct the high fidelity virtual model with the mapping of real time, it will be a new way for the equipment health management. For the existing studies for the metro ISCS, most of them are for the single device or subsystem, there is no unified dynamic health assessment framework for the multi -source heterogeneous data[3] . Taking the logic of "situation analysis--model construction--validation--countermeasure suggestions", in this paper, we build the four -layer digital twin-based assessment model and verify the effectiveness with the field data. We hope to support the intelligent metro O&M.

2. Theoretical Basis and Practical Challenges

2.1 Digital Twin and Equipment Health Assessment

Digital twin enables data-driven precise mapping between physical and virtual world. Typical layers are physical, data, model, and application. For metro equipment, digital twin can incessantly ingest sensor data, inspection records and maintenance logs of the metro equipment to simulate its operation, degradation, remaining life. Health Index(HI) is usually in 0-100, which is used to measure the deviation from the healthy situation. Before digital twin, the assessment of HI is usually a single parameter or a static threshold, which can not show the nonlinear degradation of the equipment under multi-factor coupling. The digital twin upgrades the HI from point-based to continuous dynamic[4].

2.2 Practical Challenges in Metro ISCS Equipment Management

Based on three year O&M data analysis from a metro operator, current challenges are summarized in Table 1.

Table 1 Key Challenges in Metro ISCS Equipment Management

Challenge Dimension	Specific Manifestations	Traditional Limitations
Numerous equipment types	>10 subsystems, >10,000 units	Siloed O&M, severe information isolation
Complex operating condition	Temperature, vibration, EMI interwoven	Fixed cycles ignore actual states
Low data utilization	Real-time data only for display/alarm	Historical data not mined for trends
Lack of quantitative decision basis	Relies on experience and fixed rules	No scientific metrics for precise maintenance

These intertwined challenges demand a digital twin-centered data fusion and intelligent assessment system.

2.3 Key Mechanisms of Digital Twin Empowerment

Digital twin enables the health assessment in three mechanisms: (1) multidimensional data fusion--by using unified data middleware, the data of operation, maintenance, and environment is aligned to the digital mirror in the whole life cycle; (2) dynamic threshold and degradation modeling--calculate the parameters that would be expected under the same condition, take the residuals as the inputs of HI, and use the nonlinear degradation model; (3) predictive assessment and early warning--use the LSTM to predict the trajectory of HI and to trigger the maintenance when the prediction gets near the threshold. These three mechanisms make a closed loop of "perception perception mapping assessment prediction".

3. Construction of Digital Twin-Based Dynamic Health Assessment Model

3.1 Design Principles

The model follows four principles: O&M-demand-oriented, data-mechanism fusion, dynamic and predictive, and feasible/scalable.

3.2 Four-Layer Assessment Framework

In this paper, we build a "data-driven--model mapping--dynamic assessment--early warning intervention" framework (Figure 1). In layer 1 (data perception), we collect real time monitoring, offline inspection, maintenance records and environment data and clean and normalize them. In layer 2 (model mapping), we build virtual models for some key equipment types (transformer, HVAC cabinets, gate controllers, etc.) for real time mapping. In layer 3 (dynamic assessment), we fuse the multi -source features to compute current HI and use LSTM to do the trend predicting. In layer 4 (early warning), we classify five health level and give differentiated maintenance suggestion.

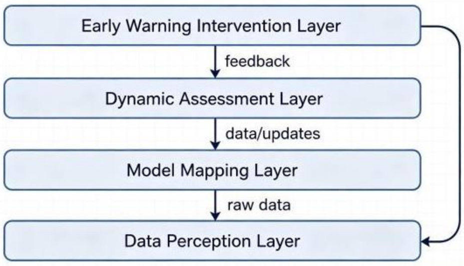

Figure 1: Schematic of the four-layer evaluation framework structure

3.3 Key Technologies and Health Assessment Algorithm

Let $HI_i(t)$ be the health index of device type i at time t, determined by operation deviation $D_i(t)$, cumulative degradation C~i~(t), and environmental correction $\gamma_i(t)$:

$$HI_i(t) = 100 - [\alpha \cdot D_i(t) + \beta \cdot C_i(t)] \cdot \gamma_i \quad (1)$$

where $D_i(t)$ is normalized Euclidean distance between real parameters and twin-expected values; $C_i(t)=1-\exp(-\lambda_i\ t_i')$ is cumulative degradation; α=0.6, β=0.4 (AHP-determined); γ>1 increases penalty when environment deviates. LSTM forecasts HI for h steps ahead. Assessment accuracy is defined as consistency between predicted and confirmed maintenance levels, with false alarm and miss rates also computed. Figure 2 shows the five-level classification and decision logic (Health≥85, Sub-health (70,85), Caution (55,70), Warning (40,55), Severe <40, with green→yellow→orange→red→dark red and corresponding maintenance strategies).

Figure 2 Health Level Classification and Early Warning Logic

4. Practical Application and Effect Analysis

4.1 Experimental Design and Data Preparation

We have conducted a 12month pilot (Mar 2025 - Feb 2026) on 15 stations of metro Line 3. 4 equipment types: power monitoring cabinets, HVAC control cabinets, gate control unit, access controllers. Data sources: SCADA parameter (every 5 min), environmental data, maintenance records, about 3.2 million records. It is the time that the digital twin platform is calibrated. Also we run the traditional threshold method in parallel. And the actual fault is confirmed by the inspection as the ground truth[5].

4.2 Health Assessment Effectiveness Analysis

Over 12 months, 87 anomaly events were detected, with 53 confirmed as true faults. Table 2 compares performance.

Table 2 Performance Comparison of Different Assessment Methods

Method	Accuracy (%)	Miss Rate (%)	False Alarm Rate (%)	Avg. Early Warning Lead Time (days)
Traditional threshold	75.3	32.1	18.9	2.3
Proposed method	95.6	8.5	6.7	7.8

Figure 3 shows time proportion distribution of four equipment type across health level. We can see that HVAC control cabinets have the worst health, which is consistent with what we often experience in practice. The proposed method improves accuracy by 17.3 percentage points, reduce miss rate by 23.6 and false alarm rate by 12.2 points, and extend warning lead time to 7.8 days.

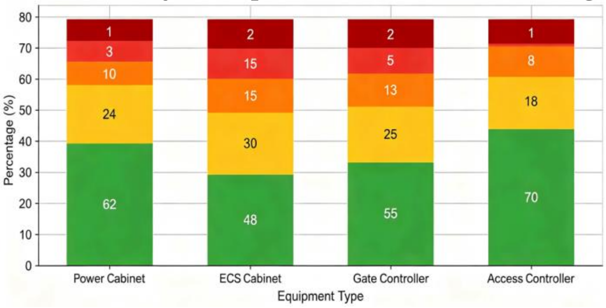

Figure 3 Health Level Time Proportion Distribution

A typical HVAC control cabinet HI trend (Figure 4) exhibits “slow deterioration→accelerated decline→recovery after maintenance→re-deterioration.”At month 8, the traditional threshold did not alert, but our method identified HI below 75 at month 7, prompting inspection that found fan bearing wear; replacement restored HI and avoided a trip fault. Figure 5 shows contribution of different features to HI decline, with current imbalance and temperature rise rate contributing most.

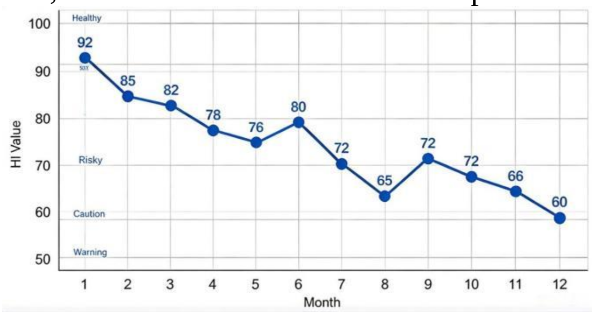

Figure 4 HI Trend of a Typical HVAC Control Cabinet

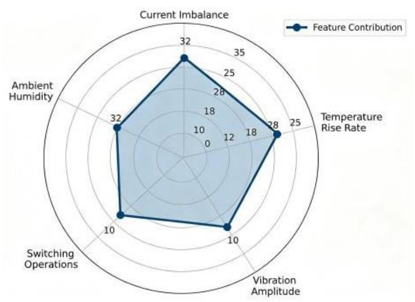

Figure 5 Feature Contribution to HI Decline

For prediction error evaluation (h=7 days) the mean absolute error of 3.2 for HI>50, relative error ~4.5%, i.e., LSTM tracks medium term trends well.

4.3 Operator Feedback

Of 15 O&M managers, 83% thought that HI is intuitive, and 76% said that the early warning reduced the pressure of emergency repair. Drawbacks: 1) that the missing sensors on some kinds of the legacy equipment results in the gap of data, and 2) the integration with work order is incomplete.

5. Countermeasures and Suggestions

In order to promote large-scale application, the following four countermeasures are proposed: (1) Strengthen data foundation: build unified data middleware, standardize the collection interface, install the missing sensors, and improve the data quality validation. (2) Dynamic model updating: calibrate the models in a quarter, adjust the degradation coefficients and the correction factors by online learning to avoid the mismatch. (3) Optimize the collaborative process: embed the health levels in the asset management system, auto-generate the work order and spare parts plan, set the threshold for the critical equipment too stricter. (4) Enhance the personnel competency: do the platform training on a regular basis, put stress on the human machine collaboration and avoid the full dependencies on the automated assessment. A pilot optimize roll out phased strategy is suggested.

6. Conclusions and Prospects

In this paper, we introduce the digital twin technology, build the four-layer dynamic assessment framework, and propose the multi- factor HI model with LSTM prediction. The empirical results indicate that the method can well integrate the multi-source data, deliver the quantitative and visualized health assessment with the accuracy of 92.6% and the lead time of 7.8day early warning, can clearly find the degradation turning points and provide the quantitative support of condition-based maintenance. The future work will extend to more equipment types, take the generative AI into the maintenance strategy simulation, and lightweight edge deployment.

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