Design and construction of a test rig for wheel-track defects diagnosis in Hefei metro

While developing defect diagnostic systems in urban rapid transit, it is not easy to experimentally obtain all the necessary input datasets under various operating and defect conditions. Alternatively, to solve this difficulty in terms of volume, variety, and velocity of datasets, a test rig is being designed and constructed using additive manufacturing while maintaining original structural characteristics in downscaling. Prior knowledge obtained from its physical and digital twins is expected to accelerate the actual development process of machine learning-based defect diagnostic algorithms through knowledge transfer from test rig to reality.

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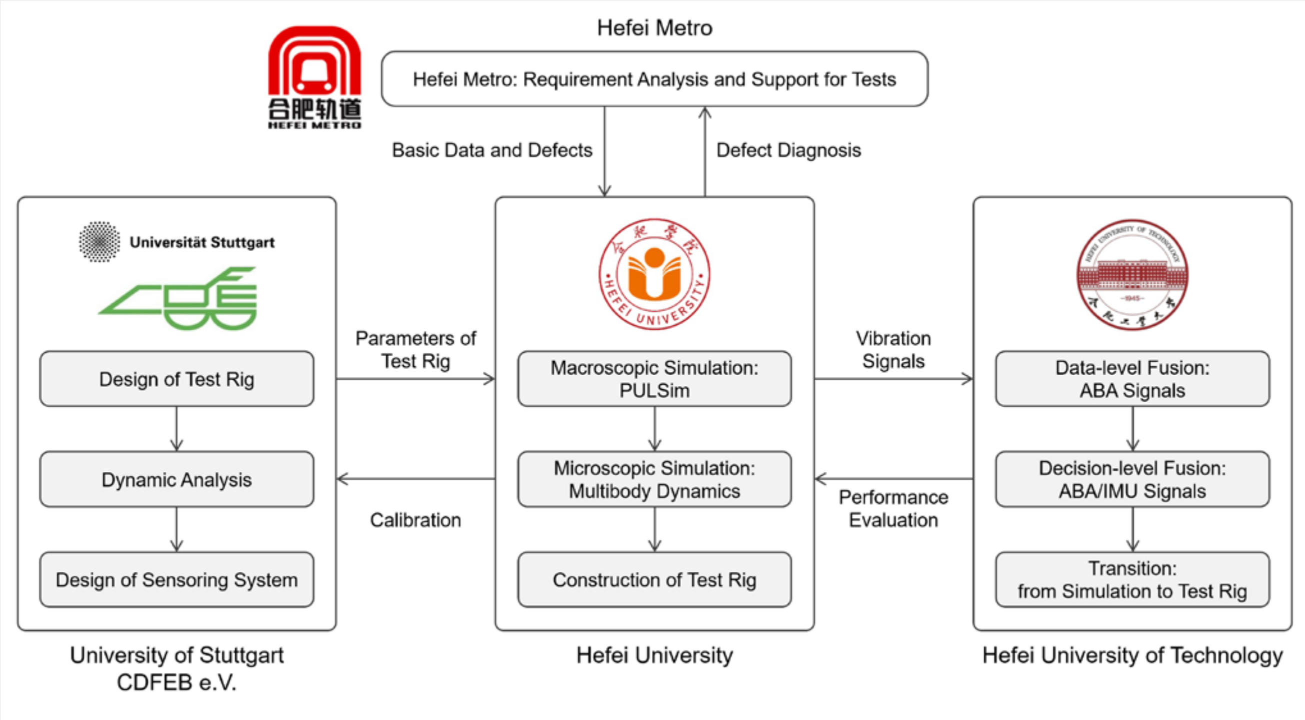
1. Introduction

Since inaccurate and unreliable inspection systems can negatively affect railway operations and maintenance schedules, many related studies have long been conducted in academia and industry to improve the defect diagnosis performance of workshop / wayside / onboard inspection systems [1-2]. Recent studies for the implementation of machine learning, in line with recent technological trends, is also gradually increasing for more accurate and reliable defect diagnosis in railway vehicles and infrastructure [3-5]. Machine learning-based approaches generally show extended defect diagnosis capabilities compared to traditional approaches such as deterministic or feature extraction-based algorithms. They require a large volume dataset, and its quality has a significant impact on defect diagnosis performance, where the quality is defined in terms of volume, variety, and velocity [6]. However, existing studies in the railway field tend to focus more on the implementation of machine learning-based algorithms rather than improving the quality of datasets. In addition, they often consider only the diagnosis of a specific single defect rather than multiple defects based on a single signal source or without sensor fusion. From literature reviews, it is confirmed that knowledge gaps still exist in terms of dataset quality, sensor fusion, and unified diagnostic algorithm, and these gaps need to be improved for better defect diagnosis performance.

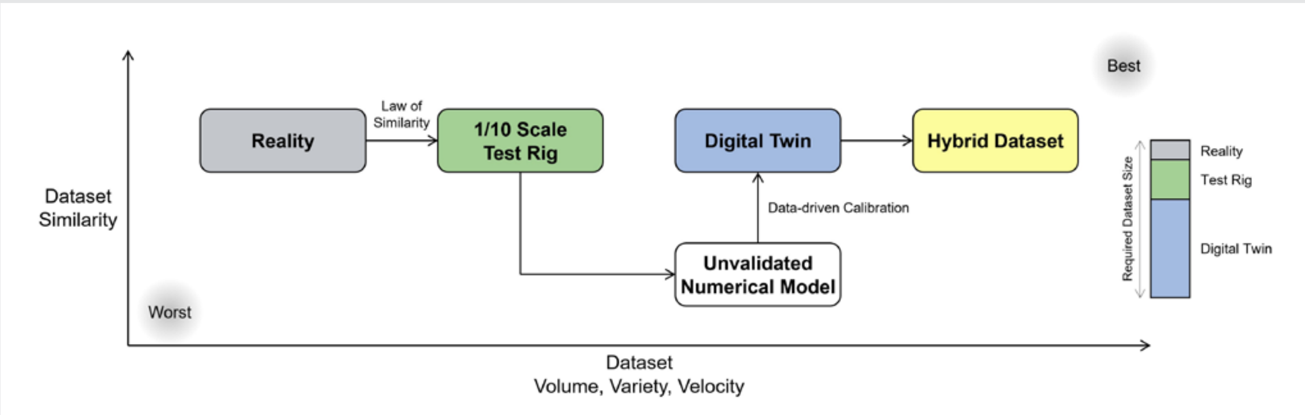
As one of the possible ways to make the operations and maintenance schedule in urban rail transit more efficient and robust against potential risks and uncertainties, this study aims to improve the limited defect diagnostic capability for wheel-track defects using wayside / onboard inspection systems and vibration sensors. Since it is generally difficult to obtain sufficient datasets from reality due to cost and time, as one of the widely used alternatives, a downscaled test rig will be used to obtain experimental datasets instead under various operating and defect conditions. The test rig consists of a vehicle with two bogies, a ballastless track, and a measurement and control system.

The main objectives are as follows:

- Design and construct a downscaled test rig while maintaining the original structural characteristics of reality in terms of the moment of inertia, dynamic behaviour, structural resonance, and coupling between structural resonances according to the law of similarity:
- Propose the law of qualitative similarity to solve weak points in the existing laws



1: Project organisation structure



2: Hybrid Dataset for better Volume, Variety, and Velocity

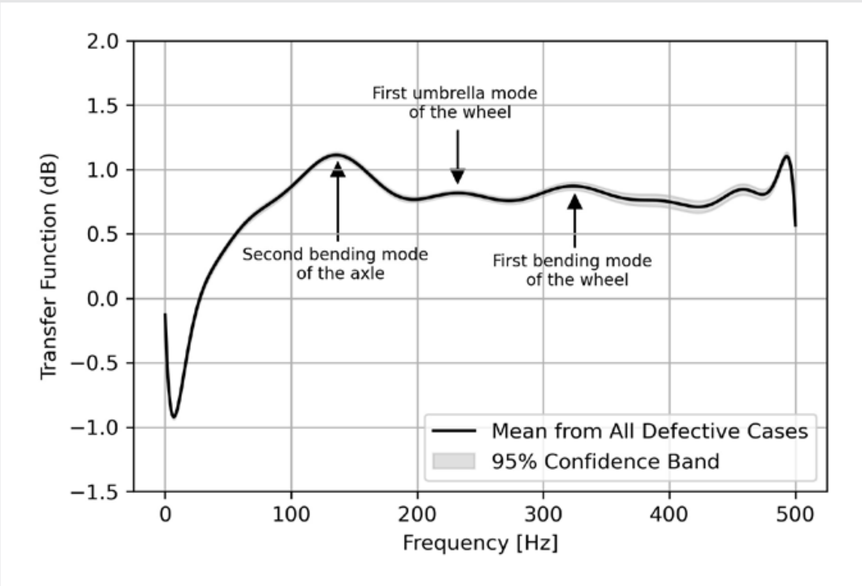
of similarity for better similarity in studies on vehicle dynamics and defect diagnosis.

- Build a digital twin by using dynamic data-driven calibration methods to approximate a vehicle-track dynamics model with flexible wheelsets and track as much as possible to experimental datasets obtained from the test rig as a physical twin.
- Develop machine learning-based defect diagnosis algorithms to diagnose wheel-track defects using the combination of experimental and numerical datasets, as a hybrid form, obtained from physical and digital twins respectively. Vibration signals will be measured from ABA (Axle Box Acceleration) sensor, IMU (Inertial Measurement Unit), and wayside sensor in real vehicles under operation, the test rig, and numerical dynamics models.
- Transfer prior knowledge obtained from physical and digital twins to reality for real-world applications and finely retrain pre-trained machine learning-based defect diagnosis algorithms with a small volume of experimental datasets obtained from reality.
- Iteration of experiences gathered from maintenance of real vehicles to improve the developed algorithms in mid- and long-term perspective.

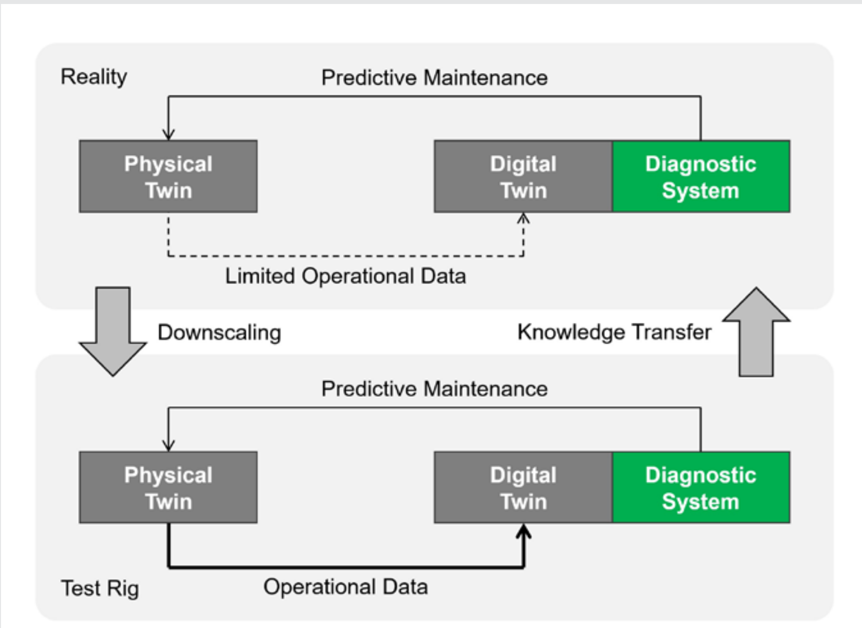
The roles of each working group in this study are divided as shown in Fig. 1. Hefei Metro provided basic data, requirements, criteria for the design and construction of the test rig and the development and verification of diagnosis algorithms for wheel-track defects. The University of Stuttgart and the CDFEB e.V. (Chinesisch-Deutsches Forschungs- und Entwicklungszentrum für Bahn- und Verkehrstechnik Stuttgart e.V.) are participating in the design of the test rig and the measurement and control system. The Hefei University is conducting numerical simulations, the construction of the test rig, and modal testing/analysis. CDFEB e.V., Hefei University, and Hefei Uni-

Table 1: Framework of vehicle-infrastructure defects diagnosis

Signal / Defect	Vehicle	Infrastructure
Vehicle	CASE I CDFEB e.V. Hefei University of Technology	CASE II Hefei University Hefei University of Technology
Infrastructure	CASE III Hefei University Hefei University of Technology	



3: Example of feature-learning capability for wheel flats in the defect diagnostic algorithm using ResNets



4: Development workflow of knowledge transfer-based defect diagnostic system

versity of Technology are developing defect diagnosis algorithms for various cases depending on the location of defect and sensor. All resources required for this study are supported by the Anhui Provincial key R&D programs, Hefei University, and Hefei Metro in China.

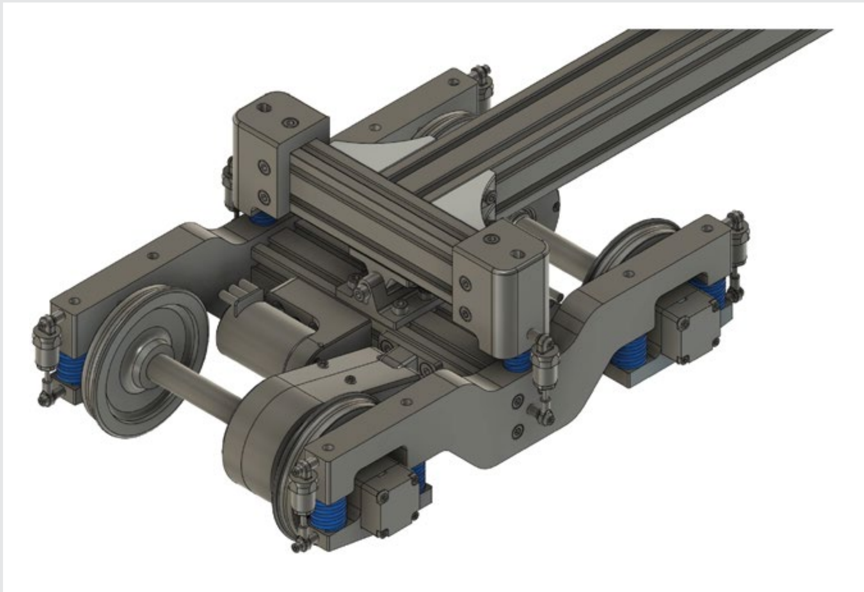
2. Development of the digital twin-based defect diagnostic system

2.1. Generation of hybrid datasets

Defect diagnosis algorithms will be developed and improved step by step based on a hybrid dataset rather than relying entirely on single signal sources, taking into account the advantages and disadvantages of each signal source. A hybrid dataset is defined as the sum of experimental and numerical datasets obtained from reality, the test rig, and the digital twin. Fig. 2 shows the relative position of reality, test rig, uncalibrated numerical model, and digital twin on the plane between volume, variety, and velocity of the x-axis and similarity of the y-axis. In reality, if there is no problem during experiments, the most ideal dataset can be obtained in terms of similarity, but in general, it is not easy to experimentally obtain a large volume dataset through fast measurement and post-processing under various operating and defect conditions as well as the actual state of different vehicles. Alternatively, if reality can be perfectly downscaled to the test rig according to the law of similarity, dynamic behaviour and vibration signals obtained from the test rig will be approximate to reality. However, there is a limitation in improving the volume, variety, and velocity of datasets through experimental approaches because compromises are inevitable in design, materials, and manufacturing methods. Thus, numerical models that are approximated to reality or a test rig have often been mentioned as a useful alternative with the keyword "Physical and Digital Twins". If numerical models could be calibrated to the level of a digital twin, their dynamic behaviour and vibration signals would be qualitatively similar to a physical twin, making it easier to meet both requirements simultaneously on the x-axis and y-axis in preparation for input datasets.

2.2. Machine learning-based defect diagnosis

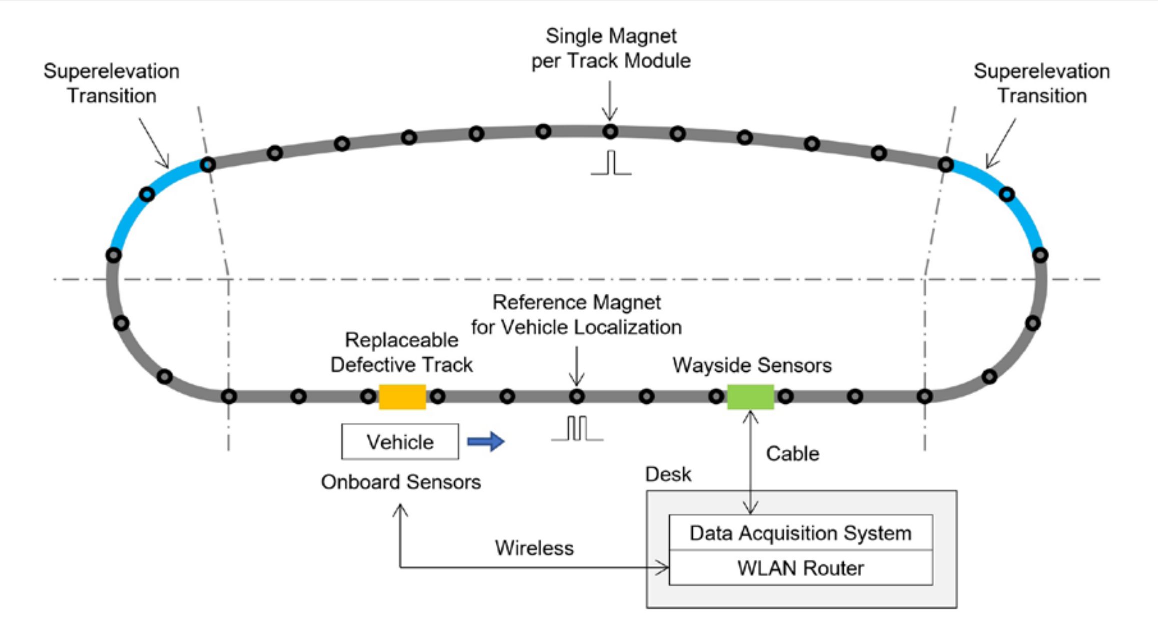
The framework for the development of defect diagnostic algorithms is divided into



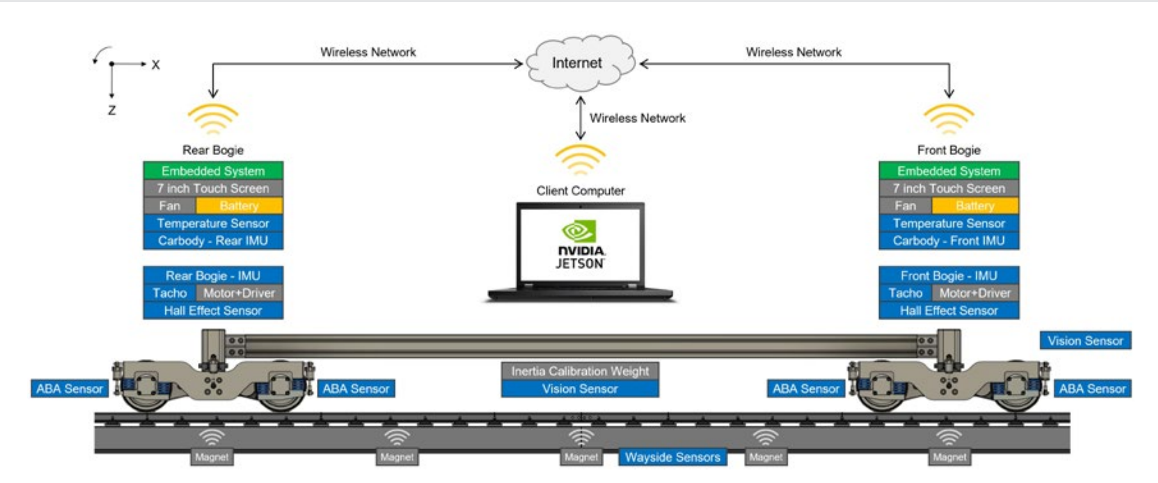
5: Vehicle model

three cases, as shown in Tab. 1, depending on the location of defects and signal sources. Case I aims to diagnose wheel defects such as wheel flat, wheel diameter difference, and wheel polygonisation using vibration signals from ABA sensor or IMU. A total of eight ABA sensors for a vehicle with two bogies are installed on the side of each axle box, respectively. The outputs are triaxial accelerations, where the lateral y-axis and the vertical z-axis are generally considered important in related studies. A total of three IMUs are installed in a carbody and two bogies. The outputs are triaxial accelerations and triaxial angular velocities. The sensitivity of IMUs to wheel defects is relatively lower compared to ABA sensors, especially in high-frequency range, because defect-induced vibration energy is significantly attenuated in transfer paths between defects and IMUs. Vibration signals will be obtained from the test rig or the vehicle-track dynamics model with flexible wheelsets and ballastless track. Case II uses vibration signals from a wayside sensor fixed on a ballastless track when a vehicle with wheel defects passes by. Vibration signals will be obtained by multiplying the transfer functions between eight wheels (all wheels of a typical two-bogie vehicle) on rail and a wayside sensor to eight wheel-rail contact forces, where the transfer functions are a function of wheel position on the track. As a vehicle speed increases, the Doppler effect also increases. Case III uses vibration signals from ABA sensor or IMU to diagnose non-uniform stiffness in slab and damages at rail joints. Vibration signals will be obtained by integrating a flexible ballastless track with infrastructure defects into a vehicle-track dynamics model. Based on experimental datasets, simulation models for three cases will continue to improve to the level of a digital twin using SIMULIA Simpack [7] and Abaqus [8].

In the process of developing defect diagnosis algorithms, neural networks can learn features that are closely related to structural defects, but traditional feature extraction techniques are often still applied to the pre-processing of input datasets without properly utilizing this capability. In addition, only sufficient accuracy and low residual errors are often emphasized without proper verification of a trained feature extraction process. Thus, regardless of case type, this study commonly aims to classify the conditions of multiple defects through feature learning on vibration signals without applying traditional feature extraction techniques to raw signals before the input



6: Layout of track model



7: Measurement and control system

layer of a neural network. For example, although important structural resonances that have a high contribution to vibration signals were not provided to researchers in the basic study for Case I, Fig. 3 shows that the important frequency range is naturally emphasized through feature learning for wheel flats in the defect diagnostic algorithm using ABA sensors and ResNets (Residual Neural Networks) [9], where the transfer function is obtained between input and pooling layers on the decibel scale. In general, the structural resonances of a wheelset and track as well as their couplings are considered important. The behaviour of vehicle dynamics in the low-frequency range, occupying the greatest energy in vibration signals, is completely filtered out because it is not closely related to the classification of defects.

2.3. Knowledge transfer from the test rig to reality

The test rig is being constructed to overcome the aforementioned difficulties in reality, but prior knowledge obtained from physical and digital twins at the level of the test rig must be transferred back to reality for real-world applications using transfer learning. There are few related studies in the railway field. The basic concept of transfer learning is that pre-trained machine learning-based defect diagnostic algorithms can be finely trained again with a small volume of datasets obtained from reality to offset gaps between reality and the test rig [10,11]. The knowledge transfer-based approach is expected to help solve the difficulty of obtaining a sufficient volume of datasets under various operating and defect conditions in reality and efficiently shorten the actual development process of diagnosis algorithms.

3. Design and construction of a test rig using additive manufacturing

3.1. Weak points in the existing laws of similarity

Related studies on the design and construction of test rigs frequently have been mentioned the law of similarity to properly connect their test rigs with reality in downscaling [12-15]. Since there is no law that can connect perfectly for all cases, the law of similarity is defined based on different assumptions according to physical variables considered important. In general, three laws are frequently mentioned in related studies, and the relationship between physical variables is not always perfect after downscaling. Therefore, related studies have been appropriately selected according to their purpose.

The three existing laws of similarity are as follows:

- The first law is defined for the same scale in time and frequency and it is widely used in related studies for vehicle dynamics on track or roller [12]. The weak point arises because after downscaling, the force and vehicle weight have different downscale ratios and the gravity remains the same as a constant. As a result, the force by vehicle weight is less downscaled than other forces. Alternatively, vertical wires are often attached to axle boxes to reduce the influence of vehicle weight and to solve this conflict.
- The second law is defined for the same scale in stress and it is used in related studies for wheel-rail contact and stress on track or roller [13]. The relationship between physical variables after downscaling coincide with modal properties well, but velocity has still the same scale. Thus, too high a vehicle velocity would be required for a study on vehicle dynamics. The test rig may be damaged due to too high stress during the test running.
- The third law is defined for non-linear vehicle lateral dynamics (hunting) on roller and it is used in related studies for vehicle dynamics [14,15]. In order for this law to be perfect, only the density among material properties must be downscaled. This conflict is solved by using a compromised value because it is difficult to decrease only the density in reality.

Even if the above laws are perfect, it is not certain that following the existing laws will maintain the original structural characteristics in the test rig after downscaling because of inevitable difficulties and compromises in terms of design, material, and manufacturing method. For this reason, this study added the concept of qualitative similarity to the first law of similarity rather than simply downscaling reality according to the existing laws. It is expected that inevitable conflicts between physical variables and compromises in design and construction can be considered more flexibly. The type of test rig is selected as a vehicle with two bogies on a ballastless track for extended studies on structural health monitoring in the laboratory environment. Basic data and dimensions for the vehicle and track was provided by Hefei Metro and downscaled to a 1/10 scale. Fig. 5 and Fig. 6 show the vehicle model and the layout of the track model respectively. According to the first law, the resonance frequencies should all be increased by ten times, but they are compromised by about 2.5 times due to the aforementioned problems in design and construction. This means that important resonances and their couplings are located at 2.5 times higher than their original frequencies while qualitatively maintaining the original structural characteristics. The sampling rate and the requirement of ABA sensors in the measurement system are determined by this relationship.

3.2. Construction of a test rig using additive manufacturing

In the railway field, test rigs have been mainly manufactured using metal machining. Recently, additive manufacturing has been widely used in the process of developing in-house test equipment in various fields [16-18]. There has not yet been a case in which additive manufacturing is considered as the main manufacturing method in related studies. Compared to metal machining, it is not easy to analyse and improve structural parts in terms of strength and stiffness through numerical simulations in the design stage due to anisotropic material properties, high-temperature sensitivity, etc. However, most structural parts for vehicle and track are being constructed using additive manufacturing because of the advantages in easy construction and modification in the laboratory environment. In addition, long printing time and anisotropic material properties, which are common problems in using additive manufacturing, are significantly improved by using the Gyroid as an infill structure and optimizing printing setups properly.

3.3. Calibration of the vehicle-track dynamics model

During the running test, track irregularities and structural defects are the main excitation sources in the test rig. The structural resonances of wheelsets and track as well as their coupling amplify these excitation sources. Except for the behaviour of vehicle dynamics at low frequency, as shown in Fig. 3, these excitation sources amplified by structural resonances occupy most of the signal energy and are also closely related to the conditions of defects. For this reason, in order to maintain the original structural characteristics in the design stage, it is necessary to numerically predict the modal properties of structural parts prior to construction, where modal properties consist of resonance frequency, mode shape, and damping ratio. However, there is a gap between actual and predicted modal properties because of the anisotropic material properties of 3D printed structural parts. Therefore, during the construction of the test rig, numerical models need to be properly calibrated based on experimental results obtained from test running and modal testing. Among available calibration methods, a dynamic data driven-based calibration method will be used because a large volume of experimental datasets under various operating and defect conditions is available from the test rig.

3.4. Measurement and control system

Just as the similarity between reality and test rig is considered important in the design and construction, the layout of the measurement and control system is also designed to be similar to actual systems. Fig. 7 shows its system layout. In the vehicle, each bogie has an embedded system (NVIDIA Jetson) for measuring signals from sensors and controlling traction motors and can operate independently according to given operating conditions. A client computer can remotely access embedded systems and then monitor and control the vehicle in real-time through a wireless network. Defect diagnosis algorithms for the three cases mentioned above will be developed as lightweight as possible to operate sufficiently in embedded systems. The vehicle location on the track will be tracked using a tacho signal from motors and acceleration signals from IMUs. Then the estimated vehicle location will be calibrated using a hall effect sensor and magnets installed at equal intervals over the track. GNSS (Global Navigation Satellite System) is not used because it has a large minimum error compared to the track size. Each bogie has four ABA sensors and one IMU. The vehicle has two IMUs in front and rear. During the running test, measurement data will be transmitted to a client computer in real-time, and then based on this data, the behaviour of vehicle dynamics will be analysed, and the condition of defects will be identified simultaneously. For further studies, wayside sensors and vision sensors will also be additionally installed. To ensure extended aspects of safety during the running test, battery temperature will be monitored too. An emergency function will also be included in the control algorithm based on vibration signals to forcibly stop the vehicle automatically in situations where the vehicle cannot be normally controlled or may be derailed.

4. Summary

This study proposes a downscaled testing platform with numerical and experimental methodologies for improving the limited diagnostic capability of wheel-track defects in urban rail transit especially. It is expected to show that prior knowledge obtained from physical and digital twins can be useful for real-world applications. The expected key contributions from this study include: (1) the design and construction of a test rig with the original structural characteristics of reality, (2) the law of qualitative similarity for solving weak points in the existing laws of similarity, (3) the dynamic data-driven calibration of a vehicle-track dynamics model for numerically generating better quality datasets, (4) the development of unified diagnosis algorithms for wheel-rail defects, (5) the development of a knowledge transfer-based diagnosis algorithm from test rig to reality.

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