RailTwin: A Digital Twin Framework For Railway

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***Abstract*— This study aims at providing a conceptualized framework for railway to realize the Digital Twin (DT) beyond traditional structural modeling or information systems. First, we deduce a generic formula that shows that DT estimates the future states and decides actions beforehand. Then, based on this formula, we design a generic framework called RailTwin. The framework combines the insight of current states, the foresight representing the prediction of the future states, and the oversight based on the current and future state to enable automation and actuation. The key enabler of this framework to obtain these states is Artificial Intelligence (AI) technologies, including Deep Learning, Transfer Learning, Reinforcement Learning, and Explainable AI. We present a use case for asset health inspection and monitoring through the proposed framework.**

I. INTRODUCTION

The railway requires a massive workforce for monitoring and maintenance purposes [1]. Nowadays, the railway industry is shifting to automotive transportation by embracing the Digital Twin technology. In an earlier period, DT gained success in the production industry for graphical modeling and data visualization [2]. The inclusion of Artificial Intelligence and the Internet of Things (IoT) has allowed DT to offer benefits beyond monitoring and simulation [3] [4]. AI technologies, such as deep learning and explainable AI (XAI), offer self-awareness and automation in the railway industry.

According to contemporary research, DT can benefit the railway in several ways including real-time data visualization [5], self-awareness [1], autonomous decision making [6], remote monitoring, and smart asset inspection [7] using AI and wireless sensing technology. The existing work has realized DT for personal vehicles like self-driving car, solar car, etc. for a specific purpose (e.g., energy monitoring). However, in complex transportation industries like railway or airport, the integration of DT is still at its early stage.

In particular the research objective our research is to design a RailTwin framework to provide the environment to monitor heavy freight cars. This allows us to develop the data-driven models through AI-Inferencing for smart asset health inspection. For this, we use detection datasets such as Wheel Impact Load Detectors (WILD) and Train Inspection Portal Systems (TIPS). Therefore, in this work, we aim to provide a conceptual framework that fits the diverse needs of the railway, in order to realize the railway DT beyond typical modeling, monitoring, and information systems.

For this purpose, we include transfer learning, deep learning, and XAI to offer foresight to predict future outcomes through predictive twin; and oversight to automate some actuation by railway DT. The key contribution of this work is two folds. i) To derive the mathematical formula to represent a generic DT framework, and ii)To design a conceptualized framework RailTwin for a multipurpose railway DT.

The rest of the section is organized as follows. In Section II we discuss, compare, and summarize the existing work to outline the problem and related requirements to design the RailTwin framework. In Section III-A, we deduce the mathematical formula as a basis of the framework. In Section III-B, we explain the RailTwin framework. A use case of the proposed framework is detailed in Section IV. Finally, in Section V, we conclude this study indicating the limitations and our ongoing work.

II. RELATED WORK

As DT for the railway is still at its early adoption stage, there are limited studies specifically on this topic. In this section, first, we present the related work on DT for railway and vehicles. Then, we discuss existing work on the autonomous train. Finally, we summarize the gaps and requirements to design a DT framework for the railway.

A. *DT for railway and vehicles*

The authors in [5] aim at providing a DT approach for accurate monitoring and controlling the electric railway power system. The main idea of this study is to collect and visualize the real-time information of multiple trains connected over a transportation network.

In [6], the authors aim to use real-time sensor data for dynamic adaptation of a data-driven physics-based DT. Their proposed approach decides which model better represents the physical state of an asset (e.g., vehicle) to classify real-time sensor data. On the other hand, The authors in [7] aim at understanding the need for Integrated vehicle health monitoring to support situation-based maintenance. They outlined that the prime enablers of DT in product life cycles are- AI, IoT, and Sensor Technology. Similar to [6], this study also discussed the relationship between digital twin and vehicle health management.

The study in [8] discusses the five-component based architecture [9] for interactive optimization of self-driving vehicles. Furthermore, the authors discuss the importance of testing AI on a controlled testbed. The authors emphasize that neural networks can be used on existing self-driving vehicles to utilize the data for decision making.

In[10], DT is used to ensure the safety and health of an electric vehicle motor to plan required service for the engine. The authors employ UbiBot, an IoT solution providing remote access and data visualization interface to monitor environment data readings from IoT sensors. The UbiBot acts as a temperature logger. The authors observed that they could access and monitor ambient temperature, light, humidity, etc., immediately through the UbiBot IoT app.

TABLE I

COMPARISON OF TECHNOLOGY, USE CASE AND VEHICLE TYPE IN EXISTING WORK

Author	Technology	Use case	Type of vehicle
Miad(2018)[5]	3D-modelling	Energy optimization	Railway
Michael(2020)[6]	Physics based modelling	vehicle health monitoring	Aircraft
Cordelia(2019)[7]	Condition based monitoring	Vehicle health monitoring	Any vehicle
Ziran(2020)[1]	Physics algorithms, Distributed network system	Traffic monitoring	Connected Vehicles
Anton(2019) [8]	Convolutional Neural Network	Safety automation	Self-driving Car
Sakdirat(2019) [5]	BIM 3D modelling	Asset maintainance	Railway
Arkadiusz (2021) [11]	IoT	Asset maintainance	Railway
Luchang(2021)[12]	Hybrid modelling using SVM	Energy optimization	Solar car
Suchitra(2019)[10]	Artificial Neural Network	Health monitoring	Electric vehicle
Ganistha(2021) [13]	AI IoT	Health monitoring, Energy optimization	Smart vehicle

In Table I, we provide a comparison of use case scenarios and technologies proposed for DT of vehicle. It can be observed from the table that most of the existing work propose DT for personalized vehicles such as solar cars. Additionally, the proposed models serve a certain purpose, such as 3D modelling or energy optimization. By contrast, very few studies propose DT for a complex and heavy duty transportation system like railway or airport. A reason behind this can be that virtual replication of a massive infrastructure poses more challenges [13].

B. Autonomous Trains

As there is limited study on DT for the railway, we also review recent studies on the autonomous train. The authors in [13] provide a comprehensive overview of scopes, challenges and existing trends of the autonomous train (AT). They found that the data collection and modeling technologies for autonomous vehicles and autonomous trains are almost similar.

Another study [14] investigated the use of autonomous trains (ATs) employing the baseline simulation model. They concluded that the railway network's capacity could be greatly expanded. However, it is acknowledged that the generated model requires further parameters, such as weather conditions, noise metrics, and constraints of processing.

The importance of a connected vehicle network to enable real-time monitoring of multiple vehicles is discussed in [15]. This research demonstrates the importance of analyzing human factors (e.g., diver's behavior) to extend system capabilities to support driver-machine- interaction.

The authors in [16] evaluate the organizational hindrance to the innovation of autonomous freight trains for large-scale deployment. They found that the economic mechanism significantly restricts innovation in rail freight transport and autonomous train operation. Therefore, the policies need to be in-lined with an innovative addition to railway transport. Similarly, in [17], authors discuss legal issues associated with an autonomous vehicle. They found it complicated to develop a suitable framework for driver-less and human-driven transportation systems. In addition, the survey of autonomous trains emphasized categorizing the features for driver-less, and driver-supported automation of train [13].

In one of our preceding works [18], the rail data from Wheel Impact Load Detectors (WILD) is used to measure the impact of the passing wheel to avoid rail brakes. A centralized data-mining system detects the impact level of moving wheels from the real-time data and notifies railway staff to take proper action. The case study of this system has been presented in another paper on our lifetime learning-enabled modeling framework for DT. In our ongoing study, we target modifying the data-mining approach for WILD through applying advanced AI learning models, such as, Transfer Learning, Deep Learning, and XAI for the Train Inspection Portal Systems (TIPS) dataset. This is because such AI learning models, unlike traditional AI models, don't require such rigorous and time consuming data engineering to build a good classifier.

As the establishment of railway DT is still in progress, it still requires reviewing certain concepts to get the complete set of requirements. Based on our studies above, we found

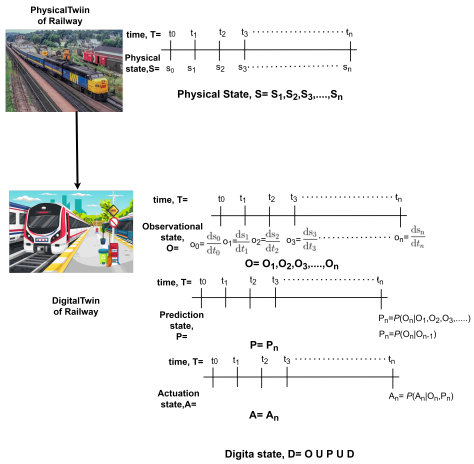

Fig. 1. Mathematical representation of physical to digital state of railway.

some common issues and requirements for a railway DT framework. Those are provided in the following section.

C. Issues and requirements

Table II provides the general issues and requirements for railway DT framework. Considering the above requirements, we deduce a mathematical formula and a generic framework RailTwin, which is detailed in the following section.

TABLE II
ISSUES IN EXISTING WORK AND REQUIREMENTS TO ADDRESS THOSE

Issues	Requirements
The load of railway industry is vast and complex to monitor and control	To include connected vehicle network to enable vehicle-to-vehicle and vehicle-to-cloud-to-vehicle communication
The models for representing or predicting all the physical state of a vehicle is hard to define.	To design a generic DT model that can fit any kind of parameters.
Data unavailability to train self-aware predictive model. Feature extraction for each of the components in a vehicle is difficult.	To include deep learning, transfer learning models for AI inferencing . To apply data augmentation as data pre-processing
A DT without explainable prediction model require further analysis and human-intervention to make the prediction usable for decision making.	To update the AI inferencing by adding XAI into it

III. METHODOLOGY

A. Mathematical formula for RailTwin

We require a fundamental formula based on which we can design the generic framework for railway DT. In this section, we present the underlying formula to mimic the physical state of the railway into the digital state. The Fig. III-A illustrates the following steps.

1) Let us consider that in physical space, the state of a railway is represented by S.
2) At initial time t_0, we get a state, s_0 at physical space, where, s_0 can be sensor reading, control action, location, asset's conditions, etc.
3) So, the physical state of railway is represented as $S = s_0, s_1, s_2, ...s_n$ at time $T = t_0, t_1, t_2, ..., t_n$ Where, t_n represents the current time.
4) At digital space, we get observation o_0 from s_0 with respective to time t_0, where, $o_0 = \frac{ds_0}{dt_0}$. The derivative is used in this equation to reflect the change of physical state (e.g., view, structure, etc.) to digital data (e.g., image, video, text, readings, etc.). For example, the real-time video (O_0) of assets present the change of physical state (s_0) at time t_0. In this example, the physical state (s_0) is different view of the assets. For instances, top-view of wheel brake.
5) The observation state of railway is represented as $O = o_0, o_1, o_2, ...o_n$ at time $T = t_0, t_1, t_2, ..., t_n$
6) Now, at time t_n, DT can forecast the observation o_{n+1}, at time t_{n+1}. Where, t_{n+1} represents future time.
7) So, the predictive state of digital Twin,P= $P(o_{n+1}|o_1, o_2, o_3, ..., o_n)$. Here probability, $P(O_{n+1})$ is a conditional probability given previous observations $o_1, o_2, o_3, ..., o_n$. One of the key opportunities of digital twin technology is: It can estimate the state in advance. The weather forecast is a suitable analogy for this predictive state in digital space.
8) Again at current time t_n, the railway DT can predict actuation based on n observations as well as predicted observations. The actuation allow the digital space to act on or control the physical space. For instance, if defect is found in any railway assets the DT can notify the decision makers. Furthermore, RailTwin can also enable or disable parts based on the condition of the assets.
9) So, Actuation state, $A = (P(A_n)|o_{n-1}, P)$ This represents another opportunity for DT. The DT can plan and perform actuation automatically based on current as well as upcoming observations.
10) So, the Physical state S of RailTwin can be represented as a collection of Predictive State, P, Observational state O, and Actuation state A.
11) Therefore, Digital state, $D = O \cup P \cup A$. So, we can observe that a DT of railway can be represented as a collection of observational state (insight), predictive state(foresight), and actuation state (oversight).

B. Proposed Framework

This section presents a conceptualized framework RailTwin to provide the DT of an asset such as a freight car or a train. The DT framework of railway contains two dimensions: the physical space, and the virtual space hosting the twins of the assets, as well as a continuous bi-directional communication flow between both dimensions. This is based on the main building blocks explained in this section. These blocks are essential to the successful operation of the digital twin framework, and are based to a large extent on the requirements analysis of the digital twin system presented in [19]. We detail here the blocks used in our framework, which are the data sensing, collection and storing; the data pre-processing and AI inferencing; and the actuation

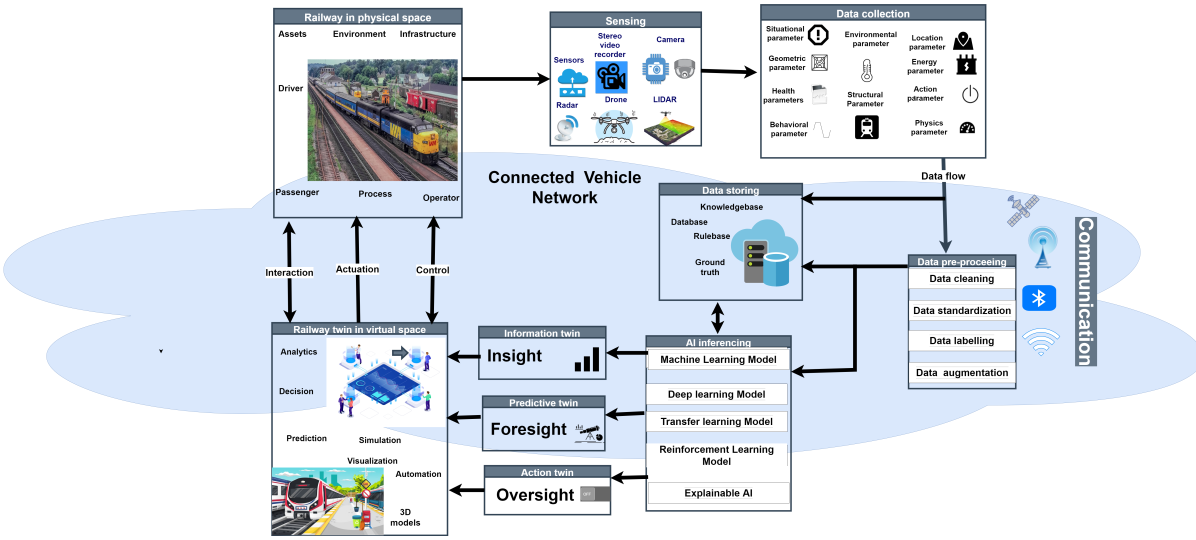

Fig. 2. Proposed RailTwin framework

and control of the physical asset. The composition of the framework is shown in Fig. 2.

The **physical space** involves *assets* (e.g., train, freights, rail-crossing, railway engines etc.), *environment* (e.g., weather, internal and external temperature of vehicle, etc.), infrastructure (e.g., railway building, automated doors, etc.), *driver*, *passenger*, *process* (e.g., health-inspection, scheduling, etc.) and *operator*(e.g., scheduler, safety monitoring officer, railway health inspector).

The bi-directional **communication** between the two dimensions of the framework, as well as the communication among the virtual twins, is maintained over a connected vehicle network. The reason behind involving a connected vehicle network is to enable vehicle-to-vehicle(v2v), vehicle-to-cloud(v2c) and cloud-to-vehicle(c2v) communication. For example, the DT framework inspects the defect of multiple freights simultaneously, based on the condition of one train, another train decides to change the route. The dedicated short-range communication (DSRC) ensures reliable Communication between the high-speed transports and its surroundings [1].

The twins of the railway at physical and virtual space interact through multi-modal interactions. Therefore, the communication direction is bi-directional in the framework. Both twins can control each other. For instance, the DT control a switch in it's physical twin (real-life railway), and an operator in the physical space can control the analytic and decision of DT to avoid system errors. The DT automatically actuates the RailTwin based on the outcomes of the AI inferencing component explained further in this section. As part of the bi-directional flow between the physical and virtual spaces, the data sensing involves the flow of data from the physical space towards the virtual one, to establish the building process of the virtual twin, and to ensure that this virtual replica remains consistent with its physical counterpart over time.

The **data sensing** process involves various sensing tools and technologies to capture observations from the physical space. Heterogeneous sensors like humidity, positioning, camera, stereo video recorder, radar, drone, LIDAR (Light Detection and Ranging) are used to sense physical space. For an example, LIDAR is used to generate an environment map to enable augmented reality and measure distance. For real-life **railway operation** the sensing technology requires to capture data of two groups [18], i) vehicle side data (like, heavy freight car), ii)track side data.

The **data collection** process collects heterogeneous parameters from the sensing process. The parameters include: *situational parameter*(e.g., vehicle mass, driver's glance, passenger's movement, passenger's expression etc), *geometric parameters*(e.g., structural patters, driver's angle, depth, etc.), *health parameters*(e.g., rust, carks, creases, fading, etc.), *Behavioral parameters* (e.g., smoky exhausts, thrums, abnormal vibration, barks etc.), *environmental parameters* (e.g., humidity, temperature, air index, etc.), *structural parameter*(e.g., length of rail-cross, material of structure, etc.), *location parameter* (e.g., vehicle position, gps location, longitudinal position, etc.), *energy parameter* (e.g., battery life, date of manufacturing, fuel consumption, etc.), *action parameter* (e.g., disable a function, start/stop a process, etc.), *physics parameter* (e.g., speed, torque, rotation, curve, etc.). For **railway operation** these data are as in Table III.

The information/status of these parameters passed as a data-flow for **data-prepossessing** as well as for **data storing**. Some of the DTs deal with raw data, and others depend on pre-processed data. Data is pre-processed in several steps, including cleaning, standardization, data labeling, and data augmentation. The data storing process also stores pre-processed data to create a rule-

TABLE III
EXAMPLE OF DATA FROM CPR RAILWAY DATABASE

Data Item	Data type	Group
WILD site information	nominal data	Vehicle side
WILD reading	numeric data	Vehicle side
TIPS	image data	Track side

base, knowledgebase database or generate ground truth. The data pre-processing and storing is one of the crucial part of predictive DT as creating DT is a data-driven process.

The **AI-inferencing** process relies on the data pre-processing and data storing. For example, a deep-learning model depends on data augmentation to deal with smaller sample sizes. AI inferencing is the heart of a railway. This process includes the following AI components.

- The *machine learning* models mainly deals with classifying, clustering, and estimating the parameters for which a huge number of historical data are available, and feature extraction are feasible.
- The *deep learning* models are used to perform unsupervised classification directly from data, without any feature extraction.
- The *transfer learning* models are employed for building models on parameters that lack a sufficient number of observations. A pre-trained model with a large number of data is retrained and re-tuned in this case.
- The *reinforcement learning* enables actuation and automation by understanding the state of a particular parameter and performing an action based on this. The reinforcement learning model mainly provides the actuation twins that support automation in control. For example, turns on the alarm, turns off a switch, etc.
- The *explainable AI* is a new addition to the DT that further advances the decision support features of DT.

The AI inferencing provides the information twin representing observational stateinsight, predictive twin representing predictive state(foresight) ahead, and actuation twin that includes actuation states(oversight) for controlling the physical railway. Overall, the railway DT includes a collection of these twins, which we have already seen in the mathematical formula in the previous section. A railway DT offers data analysis, decision support, automation, 3D modeling, simulation, and visualization in virtual space.

In an extended work of this paper we are developing the AI-inference by employing explainable deep learning model to detect defect from TIPS data. The deep learning part inclues Convolutional neural network(CNN) model. The CNN model passes each pixel of a part's image to the input layer. After that, these pixels are passed through a selected number of hidden steps. The convolution aims to perform element-wise multiplication of image pixels to recognize the image features (e.g., color intensity, pixel similarity) anywhere in the image. The CNN network scans a part of the image array and multiplies it into a filter. Finally, all the layers are connected to the next layer, known as the fully connected layer. Finally, the CNN predicts defects at the output layer. To explain the prediction, we applied the LIME algorithm after the output layer. The algorithm modifies single data points based on the feature values. The LIME algorithm split the image outputs into superpixels, where patches of the part images have similar visual features: color or brightness. A use-case of this framework has been detailed in the next section.

IV. A USE CASE: SELF-INSPECTION OF RAILWAY ASSETS

Structural defect diagnosis is a common task to improve railway assets' reliability and sustainability (e.g., rail wheels, rail crossings, etc.) This section presents a use case for diagnosing defective parts in the railway by employing RailTwin framework. The steps of the RailTwin framework are listed below.

- The physical space of this use case includes parts of the train, including- brake, wheel, gate, etc.
- Then, various states from this physical space can be sensed through visual sensing through the camera. In practice, a drone camera captures and sends real-time videos of various railway parts. Here, the views of the assets are the physical states.
- The structural parameters can be the image of parts and health parameters (e.g., defects and normal image of railway components) are collected through visual sensing for defect identification. These images are compared to the observation states.
- After that, data-prepossessing is performed to make this data usable for a defect classifier. In reality, the operational environment of the railway keeps changing and leverages new data. Therefore, sometimes the data is insufficient and imbalanced for training a defect classifier. Data augmentation can be performed by rotating and zooming the collected image data.
- These data can be stored in cloud database to provide historical data, ground truth, etc. For experimental purposes, Tensorflow data pipeline can be created for storing the data for building a sophisticated input pipeline for reusable data. The image model pipeline gathers data from files in a distributed file system, apply random modifications to each image, and combine randomly selected images into a batch for training the model.
- Then, at the AI-inference stage, the framework builds a deep-learning model to classify defected and normal parts of the rail. The Local Interpretable Model Agnostic Explanations(LIME) algorithm is used to interpret the prediction. The vehicle area which is carrying the defects is identified by marking the spot—this aids to automate the smart inspection on defect detection in railway industry. The Fig. 3 illustrates defected area identified by LIME algorithm for an image which has been predicted as a defected one by the CNN model.

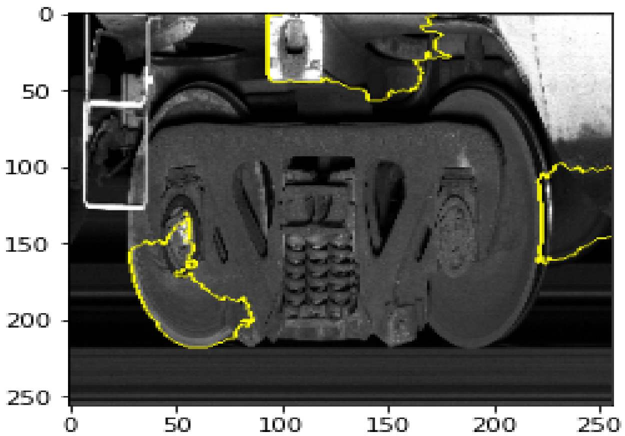

Fig. 3. Example from the experiment of our ongoing work.

- The outcome of the AI-inferencing of the DT will support decision making. For example, the railway digital twin decides which part needs replacement or repairing. The decisions are notified to the users in-order to enable replacement or repairing at the physical space. Hence, this process represents the action state.

V. Conclusion and Future Work

This research proposes RailTwin, a conceptual framework for railway digital twin. We present this framework for railway operation through DT with it's mathematical basis. Furthermore, we demonstrate some examples, from our ongoing research, to explain the framework. As DT for railway is a recent concept, our RailTwin framework is as of now still limited and can mainly detail the Data Collection and AI inferencing process. However, these two processes are core of the railway DT framework to support the key research objective here, which is the smart railway health inspection. In our ongoing studies, we further advance this research work to extend the framework, as well as to evaluate the framework for asset defect detection and monitoring using TIPS images.

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