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Integration of Building Information Modeling (BIM) and Artificial Intelligence (AI) to detect combined defects of infrastructure in the railway system

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Abstract. Due to the high demand for the railway system nowadays, the speed and load of rolling stocks tend to increase. At the same time, the effect of extreme climate is also more severe. These result in the deterioration of the railway infrastructure which causes defects to the railway infrastructure. Defects can affect passenger comfort and operating safety of the railway system. Detecting defects of the railway infrastructure in the early stage of defect development can reduce the risk to the railway operation, cost of maintenance, and make the asset management more efficient. This study aims to apply Building Information Modeling (BIM) integrated with Artificial Intelligence (AI) to develop the detection system of defects in railway infrastructure. In this study, dipped joint and settlement are used as examples of combined defects in the railway infrastructure. To detect defects, AI techniques are applied. Deep Neural Network and Convolutional Neural Network are used to develop predictive models to detect defects in the railway infrastructure and rolling stock. The results of the study show that the developed models have the potential to detect defects with accuracies up to 99% and are beneficial for the asset management of the railway system in terms of risk management, passenger comfort, and cost-efficiency.

Keywords: Building Information Modeling, Artificial Intelligence, Railway Infrastructure, Railway Defects, Dipped Joint, Settlement

1 Introduction

The demand for railway transportation is increasing [1]. The speed and load of rolling stock tend to increase. Moreover, the global warming and climate change also results in severe weather conditions [2-5]. As a result, railway infrastructure deteriorates faster and defects occur. Defects can affect passenger comfort, create some noise, or serious incidents such as derailment [6]. Detecting defects in the early stage can reduce negative effects and maintain passenger comfort, safety, and good asset management [7].

Railway inspection can be conducted in various ways such as visual track inspection [8], ultrasonic inspection [9], magnetic induction sensors [10], and eddy current [11]. Nowadays, the application of artificial intelligence (AI) is interested in being applied to defect railway defects because it is non-destructive testing (NDT), fast, and requires a lower cost to inspect railway infrastructure. Different AI techniques can be used to develop models to detect defects such as convolutional neural network (CNN), deep neural network (DNN), regression, decision tree, or random forest.

To apply AI efficiently in railway defect detection, sufficient data is required as well as data management. Building Information Modeling (BIM) is an approach to manage data throughout the project life. Integration of BIM and AI will maximize their benefits. Information of railway infrastructure components is contained in the BIM model and can be used throughout the project life.

This study aims to integrate BIM and AI to detect combined defects in the railway infrastructure. Dipped joint and settlement are used as case studies. Data is generated by using simulations from a verified software called D-Track. BIM model is developed to contain information. In this study, predictive models are developed by using DNN and CNN.

2 Literature review

2.1 Building Information Modeling (BIM)

BIM is the information management throughout the project life cycle [12]. The main role of BIM is to allow the full collaboration possible by sharing a model by every party related to the project.

BIM has been used in building construction for a long time. The development of BIM application in a building is extended to 6D [13, 14]. The application of BIM in the railway system tends to be interested however the application is relatively low. There are attempts to apply BIM in the railway system. Kaewunruen and Lian [15] applied digital twin or BIM to railway turnout in the sustainability aspect. They demonstrated effective ways to apply BIM to railway turnout in different stages through the project life cycle. Besides railway turnout, BIM was applied in railway station [16] in different aspects such as potential of a renovation of old railway stations and sustainability [17, 18].

2.2 Artificial intelligence (AI)

Artificial Intelligence or AI is “the study and design of intelligent agents’ to achieve particular purposes [19]. Examples of AI’s advantages are human error reduction, risk reduction in some tasks that need human labor, a continuation of work, good for repetitive jobs, faster operation, routine application, and good for complex questions [20].

AI can be used to optimize the speed profile of rolling stocks. Huang et al. [21] applied random forest regression and support vector machine regression to calculate speed profile and energy consumption. They found that the developed models could calculate energy consumption with an error of less than 0.1 kWh and reduce energy consumption by 2.84%. AI was used to improve railway safety at railway stations. In 2019, Alawad et al. [22] used a decision tree to analyze fatal accidents. Sysyn et al. [23] applied image processing to predict rail contact fatigue on crossings. AI is used to predict other incidents such as broken rail [24], defected insulator surface [25], and railway surface defects [26]. Mandriota et al. [27] applied machine vision to detect corrugation. Image processing was used for detecting railway defects in other studies [28-34]. The more advanced technique to detect rail defects was a 3D laser with an accuracy of 93% [35]. From the literature, it can be seen that a popular technique was image processing which additional devices were required to be installed. An advanced technique such as laser sensors also required the installation. Therefore, an alternative technique which is cost-efficient and reliable such as AI is interesting to apply for railway defect detection.

It can be seen that integration between BIM and AI has never been done in the railway system aspect. In addition, the development of predictive models to detect combined defects is limited. Therefore, this study aims to fill this gap to demonstrate how to integrate BIM and AI together and the potential of AI models to detect combined defects in railway infrastructure.

3 Methodology

3.1 BIM model development

The BIM model in this study is developed by using Civil 3D software. The BIM model developed in this study is aimed to be a 6D model to contain design, cost, time, and maintenance information. The development of the BIM model is described as follows.

The development is started from 2D drawings. Horizontal alignment and vertical alignment are shown in 2D drawings. Based on 2D drawings, the BIM model is developed using the software through a corridor which depended on alignment, profile, and assembly. The corridor is created in form of solid 3D. Then, an IFC (Industry Foundation Classes) is exported from solid 3D. From BIM model development, IFC files are outcomes which can be shown in Fig. 1.

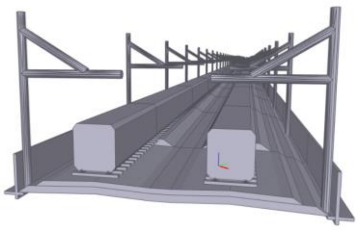


Fig. 1. Examples for BIM models hich created by using Civil 3D

The 4D model is further developed from the 3D model. In this study, the 4th D is defined as the schedule. Navisworks is used in this study to determine the project schedule. The IFC file is appended in Navisworks. Every rail component can be added as a task automatically. The created schedule is exchangeable with other schedule software such as Microsoft Project and Primavera P6. An example of a schedule which created by Navisworks can be shown in Fig. 2.

The 5D model is developed to calculate material quantity and cost. In this step, material quantity is directly affected by the subassembly definition. Quantity takeoff can be done and demonstrated in form of a table.

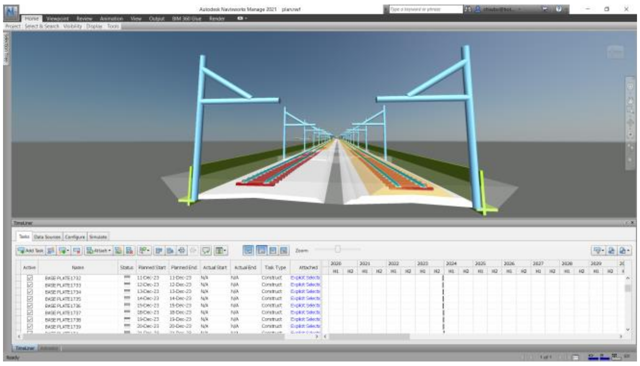


Fig. 2. An example of schedule created by Navisworks from the BIM model

For the 6D model, it is related to information management. In this study, information is used later for developing AI models. Information which contained in the BIM model as the 6th D is features for AI models. To include additional information in the BIM model, information is added through Property Set Definitions. For the ease of information management, Dynamo for Civil 3D is used.

Up to this step, the BIM model is created and ready to add information into the model. Every object in the model can contain its own information and sets of information can be different depending on the demand of use. This can be done via Property Set Definitions. The following section will present data which additionally stored in the BIM model to develop AI models and detect combined defects in the railway infrastructure.

3.2 Data preparation and characteristic

Data which used in this study is simulated by using a software called D-Track. D-Track was developed by Cai [36] in 1996 to study railway track dynamic behaviors. In 2005, Steffens [37] developed the DARTS (Dynamic Analysis of Rail Track Structure) model and its interface based on D-Track. However, Steffens found that there was a significant difference between benchmarks and models. Leong [38] improved D-Track for more accuracy until the error was less than 10% compared to actual field data. It can be concluded that the accuracy of D-Track is satisfied so it is used in this study to simulate dynamic track behavior data.

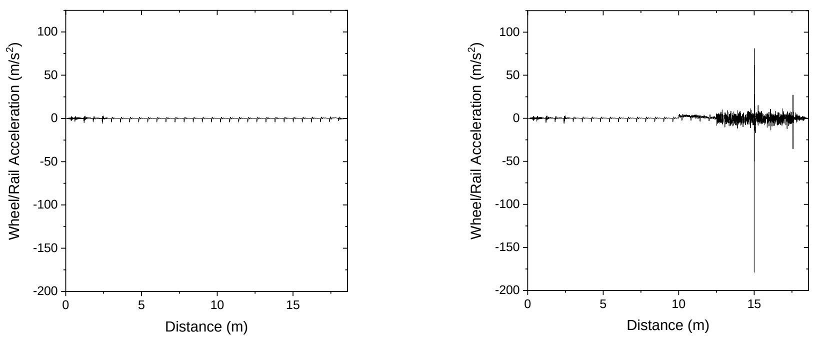
Characteristic of the railway system can be set in D-Track such which consist of track properties, vehicle properties, defect properties, and defect locations. The output of the software is various. In this study, accelerations of wheel-rail contact are used.

For simulations, different parameters are added to generate data. Varied parameters consist of sizes of dipped joint, sizes of settlement, speeds of vehicle, and weights of vehicle. A summary of varied parameters for simulation is shown in Table 1.

Table 1. A summary of varied parameters in D-Track

Parameters	Range	Step	Unit	Remarks
Sizes of dipped joint	0-10	2.5	mm.	The length of the dipped joint is 1,000 mm.
Sizes of settlement	0-100	20	mm.	The lengths of the settlement are 3,000 and 10,000 mm. for short and long settlement respectively
Speeds of vehicle	20-200	20	Km/h	
Weights of vehicle	40-80	20	tons	

From Table 1, the total number of simulations is 1,650. Examples of output from D-Track are shown in Fig. 3. From the figure, accelerations are simulated by the following parameter: speed of the vehicle is 20 km/h and weight of the vehicle is 40 tons when Fig. 3(a) shows a simulation without defect and Fig. 3(b) shows a simulation with dipped joint of 2.5 mm and short settlement of 20 mm. It can be seen that when the rail has defects, peak and bottom values are clearly identified. Note that Fig. 3 presents accelerations from a wheel only. There is another set of data from another wheel from simulations.



(a) (b)

Fig. 3. Examples of D-track output: (a) Wheel/rail acceleration when the rail is defect-free; (b) Wheel/rail acceleration when the rail has dipped joint and settlement

Generated wheel/rail accelerations are stored in the BIM model for each section of the track to detect combined defects further. This study applies DNN and CNN to develop AI models to detect combined defects. Data is used in 2 ways depending on AI techniques. For DNN, data is used as simplified data. For CNN, data is used as raw data.

In case of CNN, 2 sets of raw data are used as features. However, data needs to be processed for DNN. In this study, 14 features are used for training DNN models which consist of speed of vehicle, weight of vehicle, and 3 peak values and bottom values from 2 sets of wheel/rail accelerations. To process data and prepare data, Excel Macro is used.

3.3 AI model development

In this study, DNN and CNN are applied to develop AI models for detecting combined defects of dipped joint and settlement. This study purposes 2 approaches to develop predictive models. The 1st approach is to develop a model to detect combined defects. For the 1st approach, there are 4 classes, class 1 defect-free rail, class 2 rail with dipped joint, class 3 rail with settlement, and class 4 railway with dipped joint and settlement. The 2nd approach is to develop series models to detect dipped joint and settlement independently. Therefore, there are 2 predictive models in the 2nd approach, namely a model to detect dipped joint and a model to detect settlement. Each model has 2 classes which are with and without defect classes.

For DNN, the number of hidden layers and hidden nodes are tunned as other parameters such as learning rate, momentum, and activation function to provide the best performance.

For CNN, 2 sets of raw data are fed into models. CNN is used for feature extraction without the knowledge of feature engineering which is an important advantage of CNN. A CNN model consists of 2 parts namely the feature extraction part and classification part. Hyperparameters are tunned to make the model provides the best outcome.

Both DNN and CNN models are developed with dropout to prevent overfitting and enhance the accuracy of predictive models. 70% of the dataset is used as the training data and 30% of the dataset is used as testing data.

4 Result and Discussion

From the BIM model development, required features which used to develop predictive models can be stored in the BIM model. In this study, wheel/rail accelerations are used as features in ANN and CNN models. Speeds and weights of the vehicle are used in ANN models. Information in the BIM model can be manageable by using Dynamo for Civil 3D. When information from the BIM model is exported to spreadsheet software, it can be managed by using spreadsheet macro. In this study, Excel Macro is used to manage and process information.

To assess the performance of developed predictive models, accuracy, precision, and recall are used. As mentioned, DNN and CNN are used to develop models. The performance of each technique is shown as follows.

4.1 The 1st approach: One model for detecting both dipped joint and settlement.

There are 4 classes when this approach is used as mentioned. The performances of DNN and CNN are shown in Table 2.

Table 2. Performance of DNN and CNN for detecting combined defects using the 1st approach

Class	Accuracy		Precision		Recall	
	DNN	CNN	DNN	CNN	DNN	CNN
Class 1 Defect-free rail	0.86	0.99	1.00	1.00	0.93	1.00
Class 2 Rail with dipped joint			0.00	0.97	0.00	0.88
Class 3 Rail with Settlement			0.90	1.00	0.68	0.99
Class 4 Rail with dipped joint and settlement			0.86	0.98	0.98	0.99

From Table 2, the accuracy of CNN is clearly higher than DNN. In terms of precisions, the CNN model has significantly higher precisions than DNN. As well as recalls, the CNN model performs better than the DNN model. Therefore, for the 1st approach, it can be concluded that the CNN model is better than the DNN model to detect combined defects.

4.2 The 2nd approach: Two individual models for detecting dipped joint and settlement separately.

2 models are developed to detect dipped joint and settlement individually. Model 1 is used to detect dipped joints and Model 2 is used to detect settlements. From Table 3, it can be seen that the CNN model also performs better than the DNN model in every aspect. The recall of Model 2 developed by DNN is 0.26 which is significantly low. Therefore, it can be concluded that the DNN model should not be used to detect the settlement. From Tables 2 and 3, the overall accuracies of both the CNN and DNN models developed by the 1st approach are slightly higher than the models developed by the 2nd approach.

Table 3. Performance of DNN and CNN for detecting dipped joint and settlement individually using the 2nd approach

Class	Accuracy		Precision		Recall	
	DNN	CNN	DNN	CNN	DNN	CNN
Model 1 Dipped joint detection						
Class 1 Rail without dipped joint	0.88	0.99	0.62	1.00	0.87	0.99
Class 2 Rail with dipped joint			0.97	1.00	0.89	1.00
Model 2 Settlement detection						
Class 1 Rail without settlement	0.93	0.99	1.00	0.96	0.26	0.94
Class 2 Rail with settlement			0.93	0.99	1.00	1.00
Total accuracy	**0.82**	**0.98**				

From Tables 2 and 3, it can be concluded that, in this case, using separated models to detect dipped joint and settlement does not provide better performance. Therefore, using a single model is sufficient to detect combined defects. Based on the results in this study, the CNN model performs better than the DNN model. The CNN model can detect combined defects very accurately with an accuracy of 0.99. At the same time, both precisions and recalls are about 0.90 or higher which could be concluded that it is satisfactory and reliable to use in practice.

5 Conclusion

This study applies BIM and AI together to detect combined defects in the railway infrastructure. This study uses dipped joint and settlement as case studies. Data is generated numerically using D-Track. The BIM model in this study is developed using Civil 3D. The developed BIM model can store information which manageable using Dynamo for Civil 3D. This information is further used to develop AI models to detect combined defects.

DNN and CNN are used to develop predictive models for detecting combined defects. Information stored in the BIM model is used as features for developing models. The total number of samples is 1,650. 70% of the dataset are used as training data while another 30% of the dataset are used as testing data. It is found that CNN performs better than DNN in every aspect. The accuracies of the CNN models are almost 100%. At the same time, precisions and recalls of CNN models are about 90% or higher. This shows that CNN has the potential to detect combined defects in the railway infrastructure.

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