Enabling data-driven predictive maintenance for S&C through Digital Twin models and condition monitoring systems

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ABSTRACT

With the advancement in digital technologies and smart manufacturing, solutions for continuously monitoring the condition of Switch and Crossing (S&C) rails are being investigated. Existing understanding of the physical principles of degradation and the mechanical interaction between trains and switches can help support decisions on predictive maintenance.

Therefore, models of train-turnout interactions have been developed to support key decisions for the maintenance of S&C. A combined modelling approach incorporating Multi-Body Simulation (MBS) and Finite Element (FE) analysis of train-turnout interactions has been proposed for establishing the locations susceptible to failure and determining sensor placement. In addition, an approach for calibrating the substructure dynamic behaviour between the MBS and FE models has been demonstrated. Results for the rail receptance and contact forces obtained for the FE model have been compared with the reference MBS model and show good agreement. In the end, perspectives on transforming numerical simulation models into Digital Twins and advanced manufacturing for smart and self-monitoring infrastructures have been shared, which will no doubt be topics of future work.

INTRODUCTION

S&C accounts for just 4% of the total track mileage in the UK but attributes to over 20% of the maintenance and renewal budgets for Network Rail[1]. This is primarily due to the variation of the cross-sectional geometry in the switch panel and the presence of a discontinuity during the transition from the wing rail to the crossing. This results in a higher amplitude of wheel-rail impact forces in S&C than in continuously running rails, resulting in a higher rate of deterioration.

Infrastructure managers have been trying to bring down the cost of maintenance for S&C. With the adoption of digital technologies, data-driven predictive maintenance has immense potential for increasing safety, preventing failures, increasing route availability and reducing long-term costs. Two of the main approaches to supporting predictive maintenance of S&C through the adoption of digital technologies are automated periodic inspection and continuous condition monitoring. Data-driven periodic inspection can be supported by equipment such as unmanned aerial vehicles (UAVs) and measurement trains. However, for safety-critical systems such as S&C, continuous condition monitoring will not only improve safety but also reduce costs attributed to both failure and inspection.

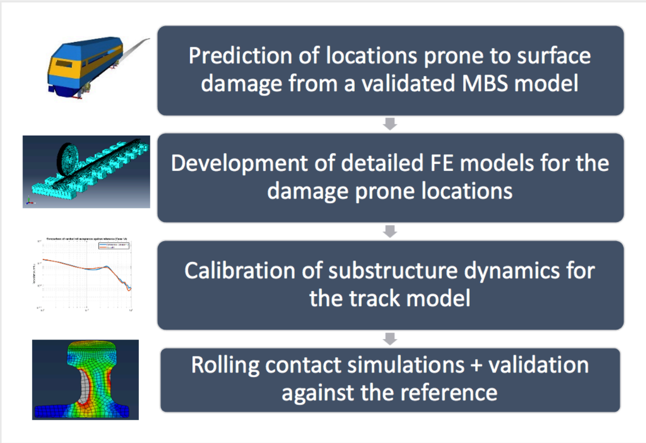

Figure 1: Simulation approach whilst considering calibrated substructure dynamics.

Currently, condition monitoring of S&C is limited to the analysis of electrical signals obtained from point machines. This approach can be used for monitoring switch opening and closure. However, this approach to condition monitoring has a limited potential for recognising the occurrence of faults away from the switch toe. Therefore, one proposed approach to gathering information about the structural health of S&C rails would be the installation of physical sensors on the permanent way itself.

There are certain challenges associated with the installation of physical sensors on infrastructure. Firstly, crucial locations on the S&C that are susceptible to failure would need to be identified. Secondly, the sensors would need to be installed to ensure that data from these crucial locations can be captured. Thirdly, the sensors would need to be robust enough to withstand the high dynamic forces associated with wheel-rail interaction. Physical sensors are already being used for monitoring the condition of structural assets such as bridges, where sensor measurements are passed to condition monitoring algorithms to obtain information about the state of health of the asset. However, harsh dynamic forces and vibrations encountered during vehicle-track interaction have made the installation of sensors on the permanent way more challenging.

For the identification of locations to monitor for failure, statistical data for failure from the infrastructure manager could be analysed. Previous inspection logs would help determine statistically significant locations that are vulnerable to failure as well as the forms of damage observed at such locations. However, where this data is not available or is challenging to acquire, numerical simulations are a potential alternative to predicting the locations prone to failure by employing formal engineering knowledge about asset degradation. Numerical simulations are powerful tools that can be used for modelling asset interactions.

Through the appropriate use of modelling approaches and knowledge from the fields of materials science, tribology, structural dynamics and mechanics, the physical interactions of the infrastructure with the rolling stock can be simulated to anticipate locations of failure. Currently, numerical simulations are also used in the rail industry to predict failure, such as the prediction of Wear and Rolling Contact Fatigue (RCF) through the Whole Life Rail Model (WLRM)[2]. The use of numerical simulation approaches for predicting the locations of failure as well as their magnitude is a topic of interest in academia and has been evaluated for S&C by the authors[3].

Research groups had previously employed a field experimentation approach to determine sensor placement at potential damage locations. It was concluded that it is unreliable to install multiple sensors and perform field experiments to determine sensor placement in harsh environments due to sensor failures, expensive site access charges and experimental setup times[4]. As a potential solution, the authors have recognised that validated numerical simulations are a safe and reliable way to generate data to determine sensor placement.

The requirement of robustness for sensors in harsh railway environments is an important consideration in enabling their installation. Along with the advancements in digital technologies, there has also been an advancement in manufacturing for the construction of smart components. Additive manufacturing of metallic components is a subject of interest in the research community, which is being actively explored for the embedment of sensors into "smart" infrastructures. Previously more popular for polymers, metallic additive manufacturing is now an area of interest in the manufacturing industry and is predicted to witness adoption at a wider scale[5].

Moreover, the availability of data related to live traffic from the field enables the transformation of numerical models into Digital Twins for S&C, where the acquired live data could be fed into models to obtain useful information for planning S&C maintenance. Historically, modelling and structural analysis were only employed at the planning stage of a project, mostly for design verification but such models can now be optimised for usage in the asset operation stage.

These challenges are being investigated through a funded PhD by the first author under the supervision of the other authors. The scope of the project includes the development of numerical simulation models that can predict the key locations for the failure of railway switches as well as determine the placement of sensors on the infrastructure. In SECTION 2 of this article, a novel approach to modelling train-switch interactions for the aforementioned research interests has been explained. The results from the simulations have been discussed in SECTION 3. In SECTION 4, potential approaches to the incorporation of these models into Digital Twins to support predictive maintenance have been conveyed. In addition, topics such as the relationship between multi-physics simulations and

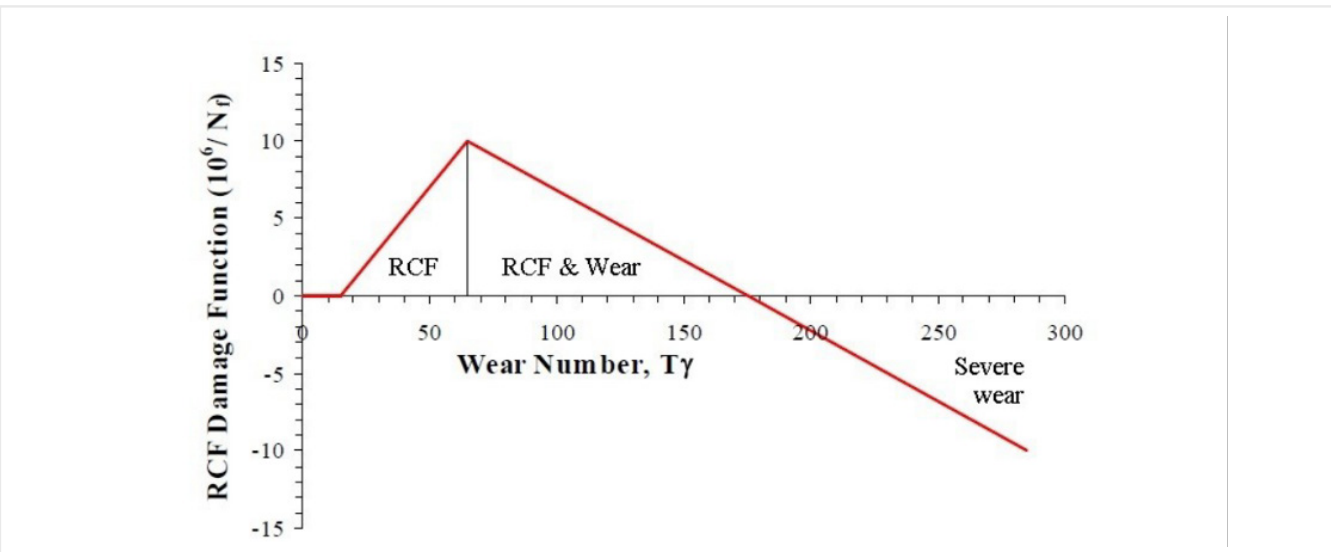

Figure 2: Bilinear RCF damage function[2] for Rail grade R260.

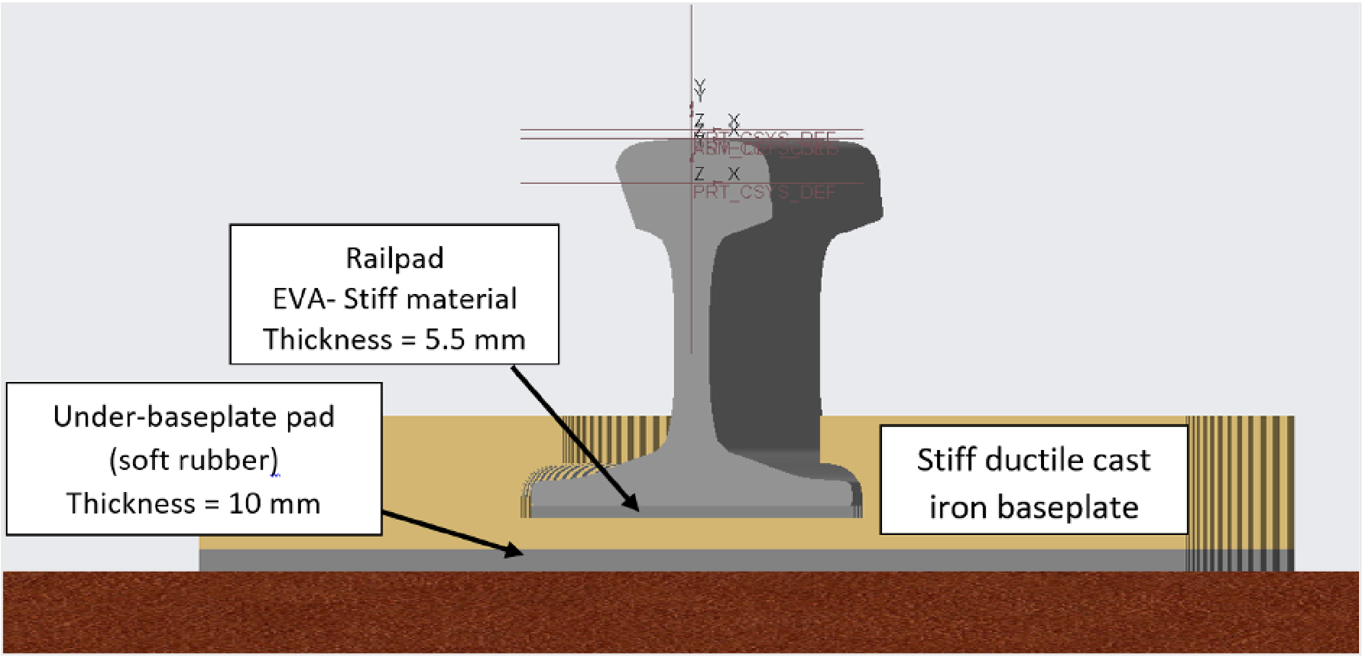

Figure 3: Rail-sleeper connection in the FE model.

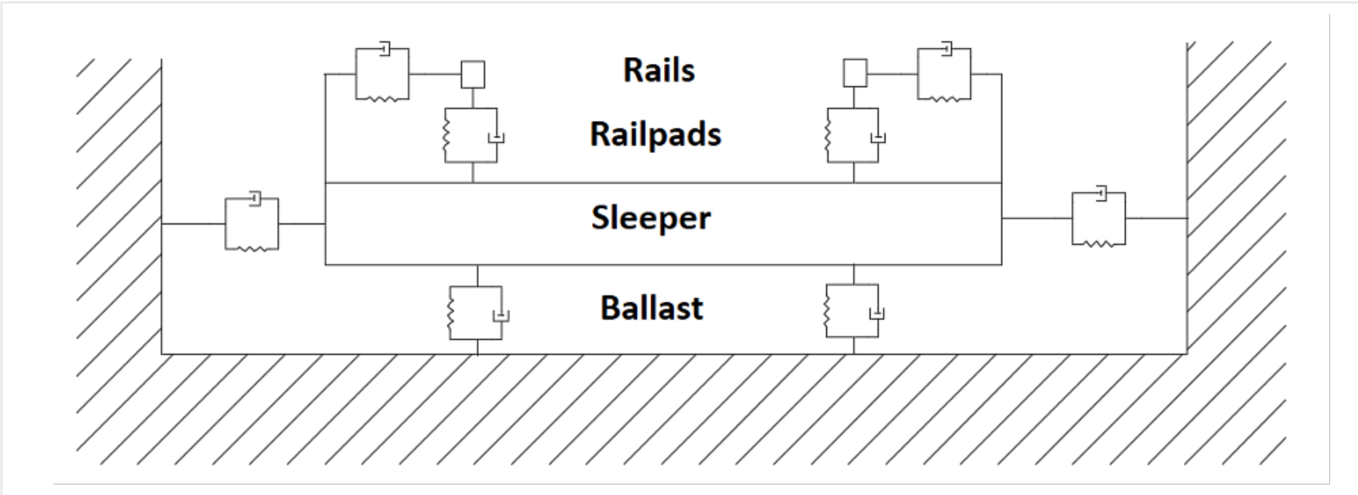

Figure 4: Connections between the different track layers of the MBS model.

sensor-based condition-monitoring systems along with perspectives on manufacturing smart rails embedded with sensors have been explored.

METHODOLOGY FOR MODELLING THE INTERACTION BETWEEN TRAINS AND RAILWAY SWITCHES

In a recently published article[3], the authors had discussed that among the main numerical approaches for simulating train-track interactions, Multi-Body Simulations (MBS) and Finite Element (FE) analysis could be used to effectively model the detailed train dynamics and mechanical behaviour of the subsurface material respectively. In literature, the results from these simulation approaches have been used in degradation prediction models to predict damage locations as well as quantitative degradation. The results from the simulations have also been validated against field observations.

We have used the results from our evaluation of train-turnout modelling approaches for the development of a combined simulation approach that involves carrying out simulations using both MBS and the FEA methods. The proposed simulation approach, shown in figure 1, has been used for determining the locations along the length of switches that are susceptible to surface damage as well as the installation of sensors for detecting the development of faults at the predicted locations.

STEP 1: PREDICTION OF FAILURE-PRONE LOCATIONS BY POST-PROCESSING OUTPUTS FROM A VALIDATED MBS MODEL

The focus of this research has been on the initiation of surface damage, especially rolling contact fatigue (RCF) cracks, since they propagate further into the rail subsurface and lead to different failure mechanisms. Another reason for focusing on surface-initiated faults is the suggestion that surface wear and fracture are the main forms of damage in switches that have historically contributed the most to delays as well as maintenance and renewal costs[1]. For the calculation of surface damage, the wear number, Tγ, has been calculated from the summation of the creep forces and creepages in the longitudinal, lateral and rotary spin directions obtained from an MBS train-track interaction simulation. The wear number can be correlated to the wear and RCF occurrence according to the empirical linking of the bilinear RCF damage function to the wear number by Burstow[2], as shown in figure 2. Also, the critical values of Tγ are dependent on the rail material.

For Rail grade R260, a comparison of the Tγ values against field observations (figure 2) determined that values of Tγ less than 15 J/m would result in no damage. Values between 15 to 75 J/m would indicate locations prone to RCF. Values between 75 and 175 J/m would indicate a reduction in RCF and an increase in wear, and values greater than 175 J/m resulted in excessive wear, resulting in the removal of any surface initiated RCF cracks[6]. In contrast, excessive wear would potentially occur for R350HT rail steel only when Tγ>400 J/m[6].

Simulations were carried out for the interaction between a passenger vehicle model[7] and a railway switch model for the Swedish turnout layout of UIC60-760-1:14[8] whilst considering Rail grade R260 material. The wear number was calculated based on the outputs from the model developed for the S&C multi-body simulation[9].

STEP 2: DEVELOPMENT OF FE MODELS FOR THE TRACK AT FAILURE-PRONE LOCATIONS

Unlike MBS simulations, the material mechanics of the subsurface rail can be analysed through the FE approach. This information is crucial for the determination of sensor placement and other studies related to the subsurface rail.

As the consideration of detailed vehicle dynamics has often been ignored in FE modelling to improve computational efficiency[3], the use of combined MBS-FE simulations has been observed in literature to alleviate this. In this combined numerical simulation approach, crucial information from the train-turnout dynamic interaction is obtained from MBS simulations and exported to FE for further analysis.

A lack of compatibility between the track dynamics of MBS and FE models has been observed from the examples in literature[3]. This is important to consider, as the stiffness of the track is higher at locations where the rail is supported by the sleeper than it is where there is no support. Moreover, at supported sections, a turnout with softer pad support for the superstructure and softer bedding would allow for more vertical movement of the rails than when the support is stiffer. Therefore, the calibration of the track stiffness against the field or reference models would help ensure the validity of results for similar conditions.

To address this gap in the literature, a combined simulation approach has been used that involves the substitution of results for the movement of the vehicle obtained from the MBS model to the FE model whilst ensuring compatibility of the track models between the two approaches.

In the FE model, the stock rail was supported by a railpad, affixed on a baseplate, which was connected to a baseplate pad, placed on a sleeper, all lying on a ballast bed which was fixed to the ground, as shown in figure 3 and figure 5. The switch rail was directly mounted to the baseplate (figure 5). However, in the MBS model, the rails are supported just by two layers, with the railpad connecting the rail and the sleepers following the ballast connecting the sleepers to the ground.

Therefore, to ensure compatibility between the two track models used in MBS and FE, the equivalent stiffness of the combination of railpad, baseplate and baseplate pad layers in FE (figure 3) was compared against the stiffness of the railpad layer in MBS (figure 4). Subsequently, the stiffness properties for the railpad, under-baseplate pad and ballast layers were obtained from Network Rail standards and used to calculate the equivalent elastic modulus for the materials at these layers.

Depending on the frequency range at which they contribute to resonance, the material damping behaviour for the pads and ballast were fine-tuned against the reference model. For this, the Rayleigh damping coefficients were calculated.

For the inclusion of the appropriate dynamic effects for the ballast layer, several proposals were explored. One solution explored the consideration of vertical and lateral spring-dashpot elements attached to the sleeper end surfaces to account for the ballast layer. Another explored the consideration of a solid ballast layer whilst converting stiffness and viscous damping used in MBS into the material properties of equivalent elastic modulus and Rayleigh damping to replicate the dynamic behaviour in FEA. The receptance from both the modelling approaches were obtained and compared.

STEP 3: CALIBRATION OF TRACK SUBSTRUCTURE BEHAVIOUR AND TRACK MODEL VALIDATION

On the derivation of the material properties, the rail receptance, ie deflection of the rail on the application of a unit load was compared between the MBS and FE models for the frequency range of interest. For components modelled using solid elements, ie the railpads, underbaseplate pads and ballast, sensitivity analysis for the damping loss factor was carried out for fine-tuning the damping behaviour with the reference. Analysis was also carried out using spring-dashpot elements to represent the ballast layer, where the values for the stiffness and the viscous damping could directly be divided by the number of nodes representing the interface surface.

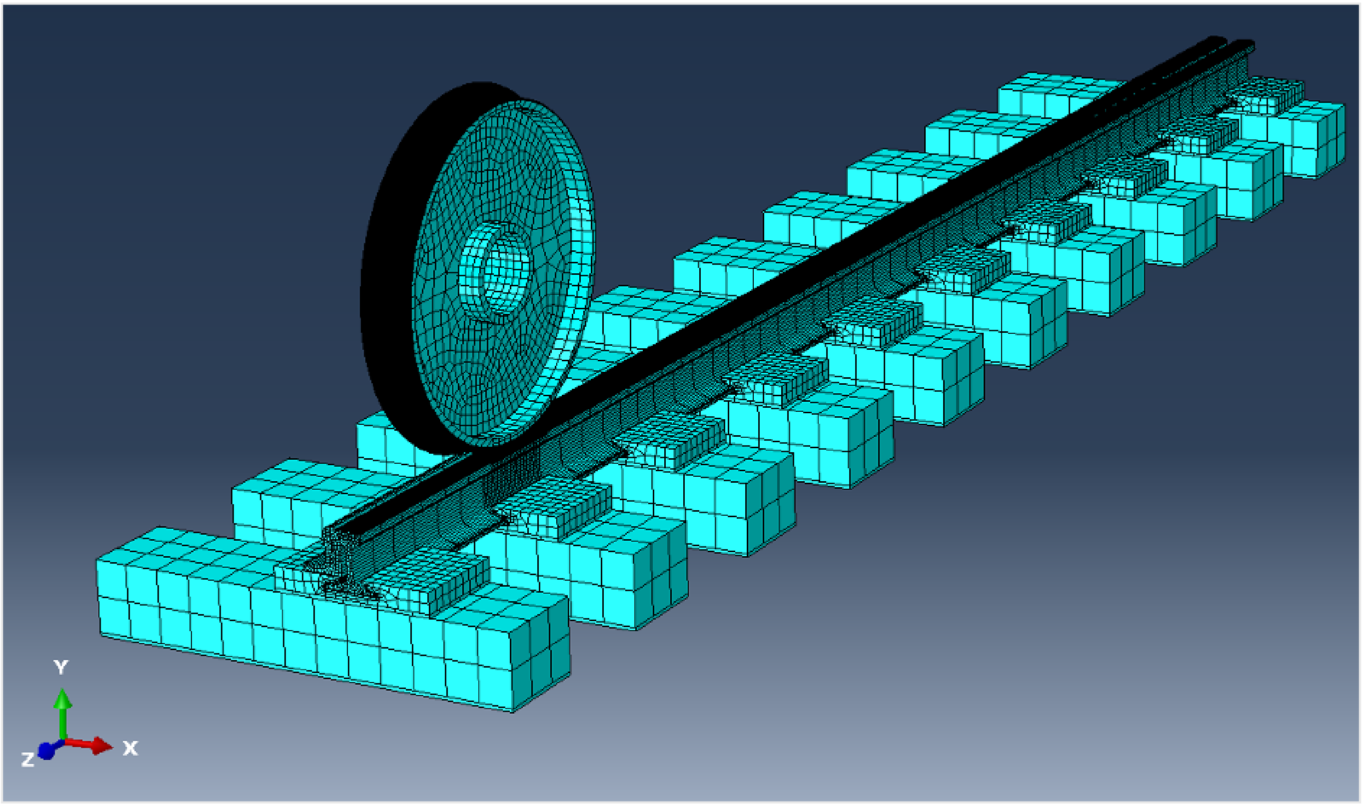

Figure 5: 3D FE model assembly for rolling contact simulations.

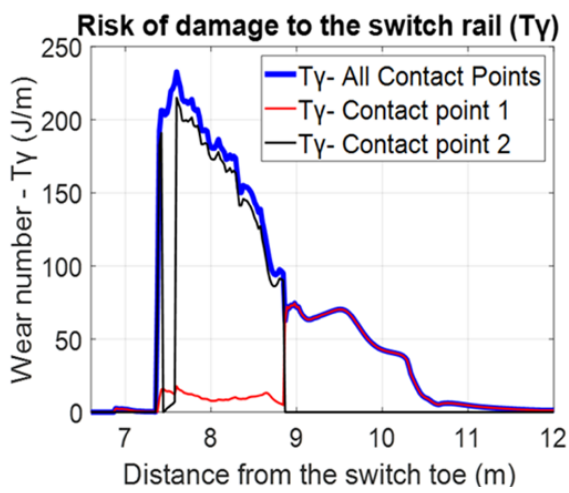

Figure 6: Prediction of locations susceptible to high surface damage.

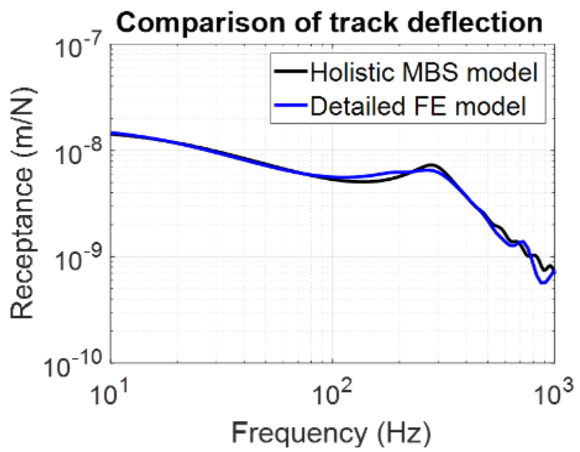

Figure 7: Compatibility of track dynamics between the MBS and FE models.

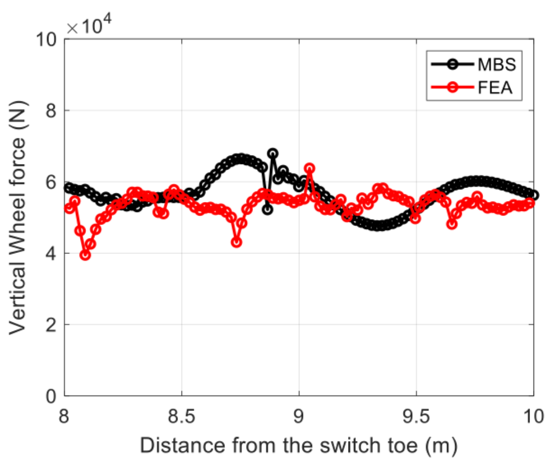

Figure 8: Comparison of vertical contact forces in the region of interest.

STEP 4: ROLLING CONTACT SIMULATIONS AND VALIDATION AGAINST THE REFERENCE.

Once the compatibility between the substructure behaviour of the MBS and FE models was ensured, Finite Element rolling contact simulations were carried out. The dynamic interaction between a single S1002 wheel passing over the stock and switch rails in the transition region of the switch panel (figure 5) was performed. Appropriate boundary interactions between the different layers of the track as well as the contact between the wheel and rail-head surfaces were ensured.

The results from the lateral and longitudinal movement of the wheel obtained from the MBS model used in STEP 1 were input as the variable boundary conditions for the wheel in FE. The FE model was validated by comparing the contact force results against the MBS reference model. Along with the validity of the surface contact results, it was also ensured that converged results were obtained for the mechanical behaviour of the subsurface rail elements.

DISCUSSION OF RESULTS: PREDICTION OF DAMAGE LOCATIONS

The locations susceptible to high railhead wear and surface-initiated RCF were determined from MBS simulations of train-turnout interactions. On the comparison of the influence of the passage of different wheelsets, it was observed that interaction of the switch with the leading wheelset would result in the highest surface damage. The result for the wear number, 'Tγ', obtained from the passage of the first wheelset of the two-bogie vehicle has been shown in figure 6.

High values for the Wear number were obtained at the location between 7 and 9 metres (m), where the wheel-rail contact patch transitions from the stock to the switch rail. Also, two-point contact was observed at this location. Contact point 2 (CP2) occurs between the wheel flange and the switch rail gauge corner. Contact point 1 is the point of contact between the wheel tread and the railhead, which was shown to move towards the rail gauge corner but later returns to its nominal position close to the railhead centre after stabilisation of the wheelset lateral movement. According to the bilinear RCF damage function (figure 2) by Burstow[2], the highest risk of surface-initiated RCF has been obtained between 9 and 9.5 m from the switch toe, where the wear number is close to 75 J/m.

DISCUSSION OF RESULTS: CALCULATION OF THE MATERIAL PROPERTIES AND VERIFICATION OF TRACK STIFFNESS

As shown in figure 7, good agreement between the vertical rail receptance for the MBS and the FE model was achieved for the frequency range of 10-1000 Hz, ensuring that similar substructure dynamic behaviour will be considered for the rolling contact analysis in the FE model as the MBS model.

DISCUSSION OF RESULTS: VALIDATION OF THE FINITE ELEMENT MODEL THROUGH COMPARISONS WITH THE REFERENCE MBS MODEL

The vertical contact forces from train-turnout interaction in MBS and FE for the same wheelset have been compared in figure 8. On the whole, a similar amplitude for the vertical contact force has been observed. The differences observed along the length could be attributed to the consideration of detailed vertical suspension dynamics in the MBS model and the application of a constant axle load to the wheel centre in the FE model, making the FE results more stable.

FUTURE WORK AND PERSPECTIVES ON DIGITAL TWIN MODELS, CONDITION MONITORING AND SMART COMPONENT MANUFACTURING

Inputs from actual railway operation such as train speeds, the number of passengers/axle loads and wheel-rail frictional conditions can transform the numerical models for train-turnout interactions into Digital Twins. However, there are certain limitations to achieving that.

One limitation is that accurate and detailed simulation for multiple degrees of freedom would result in poor computational efficiency.

Therefore, to develop a systems-level Digital Twin, reduced-order modelling techniques could be used. Reduced-order modelling would need an initial investment of computational time and inputs from numerous validated full Finite Element simulations. Once this large amount of validated data is obtained, computationally efficient and accurate numerical simulations within the boundaries defined by the full FE simulations can be carried out.

For the state of the art reduced-order modelling approaches for Finite Elements, it is currently not possible to account for geometry change, including change in rail profiles, which influences the contact locations and thus the results from the train-track interaction. Certain solutions such as scanning the rail geometry and updating the model once the maximum level of degradation is reached can be explored to overcome these hindrances. These limitations prevent the models from performing as unverified standalone solutions to inform predictive maintenance. One way of validating the models would be through comparing the corresponding measurements obtained from sensors, for example, strain gauges, which will not only help determine the validity of the Digital Twins but also provide inputs to algorithms to detect, diagnose and predict failures.

The validity of a Digital Twin model would depend on the comparison of the simulation results against equivalent outputs measured from the installation of sensors in the field. Similarly, the validated Digital Twin models can help to inform the best locations to place the sensors to detect specific failures on certain routes. In essence, Digital Twin models can support predictive maintenance either directly by predicting degradations or indirectly by informing sensor locations. The similarity in information between the fault and surrounding locations can be used to inform and optimise sensor placement, which is another question addressed by this PhD. In this way, the anticipated traffic on a given route could be used to generate simulation-based data to predict ideal sensor placement locations through Digital Twins.

The relationship between Digital Twin models and condition monitoring systems has been highlighted in figure 9. The Digital Twin model and condition monitoring system can both predict failures using mechanical degradation models and sensor outputs respectively. In addition, the condition monitoring system can perform actual detection and diagnosis of fault occurrence and the Digital Twin model could help optimise the proposed locations to place the sensors for effective condition monitoring.

For the installation of sensors on the asset, ongoing research on advances in additive manufacturing has demonstrated its potential to effectively package and manufacture embedded sensors. Forming procedures in additive manufacturing such as Selective Laser Melting (SLM) and joining procedures such as Laser Metal Deposition (LMD) have the potential for use in additively manufactured packaged sensors. However, there are challenges associated with additive manufacturing that need to be addressed through research. One is the higher strength and stiffness in the build-up direction than others, making it important to optimise the microstructural material behaviour when applying it to high loading and dynamic environment such as vehicle-track interactions. Another is high costs due to its current use in niche applications of high-value manufacturing and rapid prototyping. However, the fatigue life of sensors can certainly be improved through effective packaging and embedment and several questions can be answered through researching metallic additive manufacturing for railway applications.

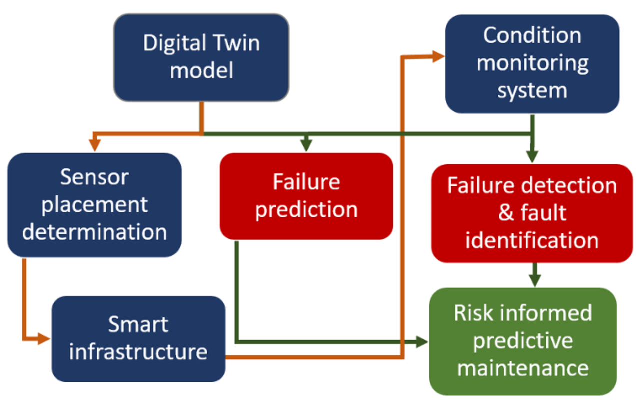

Figure 9: Data-driven approach to predictive maintenance for S&C.

CONCLUSIONS

The article highlights approaches that could potentially revolutionise the maintenance of S&C. Perspectives on realising data-driven predictive maintenance of S&C have been shared. A combined MBS-FE simulation approach to simulating the interaction between trains and turnouts whilst considering the effect of vehicle dynamics and analysis of subsurface mechanical behaviour has been described. This approach involves the calibration of the substructure dynamic behaviour between the simulation models. The results obtained for the prediction of locations susceptible to surface damage have been discussed. Comparison of rail receptance between the MBS and FE models demonstrate the validity of the proposed approach to accomplishing similar track dynamic behaviour between the MBS and FE models used for co-simulation. The vertical contact forces between the MBS and FE models have also been compared. Therefore, the FE model can be used for further studies for the subsurface rail mechanical behaviour.

With the availability of key input data, numerical models could function as Digital Twins to add value to asset maintenance through failure predictions and enhancing condition monitoring through sensor placement optimisation. Infrastructures that are smart and self-monitoring will be enabled through embedding sensors into them using additive manufacturing processes. These approaches based on data acquisition and simulation will help reduce maintenance costs, improve the safety and reliability of S&C.

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