A methodology to manage the complexity of a nonlinear multibody digital twin in railway applications

Betty Auzanneau[1,2], Emeline Sadoulet-Reboul[1], Emmanuel Foltête[1], Guillaume Ham-Livet[2], Scott Cogan[1]

[1] Department of Applied Mechanics
Institut FEMTO-ST, Université de Franche-Comté, SUPMICROTECH, CNRS
25000 Besançon, France

[2] ALSTOM Transport SA
71200 Le Creusot, France

ABSTRACT
In the railway industry, digital twins based on nonlinear multibody simulations are developed to provide decision-making support for bogie design. A recurring challenge in the use of numerical simulations is to find an acceptable compromise between the complexity of the models for the different components – in terms of their capacity to adequately reflect specific physical effects – and the associated computational burden, so as to ensure a sufficiently accurate representation of the global dynamic behavior a train. This requires an investigation into the extent to which, for instance, the stiffness and damping characteristics of a component depend on parameters such as the displacement amplitude, the frequency or the load direction. Intensive experimental studies are one strategy for increasing the knowledge of components, but they are costly to implement or incomplete when parametric dependencies are not explored. It is then necessary to determine which factors need to be controlled for each component, and to what extent, in order to prioritize them. In this context, the objective of the proposed work is to investigate different modelling strategies integrating the complexity of a physical model in different ways, and to discriminate between the effectiveness of these strategies in faithfully reproducing the dynamic responses of a structure. Two approaches are investigated in particular to study a real yaw damper component of a motor bogie. Firstly, a rheological model representing the dynamic behavior of the damper is proposed, and the parameters of this model are identified on the basis of characterization tests. This physics-based model is integrated into dynamic simulations for sensitivity studies in order to identify the influential elements that need to be controlled to validate the dynamic model. A simulation-based sensitivity indicator is developed as a tool to implement the necessary complexity for each component and to optimize the design of the required experimental studies and the methodology is illustrated for the yaw damper component mounted on a locomotive's motor bogie. In a second phase, an alternative model based on a multi-layer perceptron neural network is proposed to improve the computational efficiency of the digital twin.

Keywords: Sensitivity indicator, nonlinear multibody simulations, parametric model, data-driven model, railway application

INTRODUCTION
The railway industry is a sector in which the search for performance and safety is an essential part of the design process. The growing use of digital twins is opening up new and unexplored avenues both in the preliminary design phase and in the final phase when railway vehicles are homologated. The bogies at the interface between the bodies and the track are critical components ensuring the stability and comfort of trains, and nonlinear multibody simulations provide assistance in the choice of suspension components at the design stage in order to guarantee good overall dynamic behavior of the train. A recurring challenge in the use of numerical simulations is to find an acceptable compromise between the complexity of the models and the associated computational burden. Simplified models may not accurately capture complex dynamic behavior, while models that are too detailed may incur prohibitive computational costs and be unusable in practice. In this context, the purpose of the research work is to investigate the level of model complexity required to validate the dynamic model of a railway vehicle and a specific component of a bogie, in this case a yaw damper, is considered. This question is both related to the problem of modeling, largely investigated in the railway domain by [1] and of quantifying model-form error that has been a topic of recent investigations, for example [2]. Two approaches are considered in this study. First, a physics-based model is

developed using a rheological model for the yaw damper. Even if some references introduce 3D geometrical models for such components [3] [4] [5], models based on combination of viscous elements, springs, and dashpots are widely used, and well-adapted for multibody simulations [6] [7] [8]. An automated procedure is used to determine a set of feasible values for model parameters in order to approximate the measured behavior of the component and a decision-support indicator for the model complexity is introduced. Secondly, an AI-based method is introduced to develop a simplified model, with reduced computational times. Neural networks are an emerging strategy to define input-output relations for complex components presenting nonlinear behaviors [9] [10]. The behavior of the damper is represented by a multi layer perceptron neural network expressing the complex relationship between force, displacement, velocity and acceleration at the component interfaces and experimental validation is performed in order to evaluate the model's fidelity-to-data.

PRESENTATION OF THE STUDY-CASE

The yaw damper presented in Figure 1 is characterized using a traction-compression machine. A series of 30 tests are preformed imposing a mono-harmonic displacement excitation at various amplitudes and frequencies and the measured force data show a nonlinear behavior of the component depending of the amplitude and frequency of the excitation. The post-processing of the experimental results allows to compute the global mechanical characteristics (the macro values): the complex dynamic stiffness amplitude and the loss factor. To differentiate the component behavior with the macro values, a third characteristic based on the force-displacement hysteresis shape is added.

(a) (b)

Fig. 1 Experimental bench used for the yaw damper characterization (a). Rheological model of the yaw damper (b).

A COMPLEXITY LEVEL DECISION SUPPORT INDICATOR FOR THE RHEOLOGICAL MODEL

Determination of the rheological model parameters

Figure (1b) illustrates the yaw damper modeling using a rheological model inspired by two conventional Maxwell models. The nonlinear damping parameter F_{c1} is expressed using the experimental values. A set of values for the linear stiffness parameters k_1 and k_2, as well as the linear damping parameter c_2, representative of the damper behavior, can be found using an exploratory phase that is defined in three steps. The process begins with the generation step is the generation of a sample of the k_1 k_2 and c_2 values. Next, the simulated behavior of the component is calculated using these values and the resulting macro values are obtained. Finally, the latest values are compared with accepted tolerances and the sample is rejected if declared unsuitable.

Modeling level decision support indicator

The yaw damper model is integrated in an early design phase of a high-speed train locomotive model and 44 output features of interest are defined to quantify the operational safety and the comfort of the railway vehicle. The objective is to determine the influence of the rheological model parameters on the output features and to determine whether the model can be simplified. A variance-based sensitivity indicator using the previous sample based macro values tolerances is computed and allows to rank the parameter influence on the outputs. The results are displayed as a color matrix in Figure 2 and demonstrates that, for outputs 10, 12, and 16, the parameter k_1 has the largest impact. This suggests that the model could be simplified by eliminating the secondary Maxwell branch; which is not actually possible due to the output 39 indicator which indicates that the parameter k_2 has the highest influence.

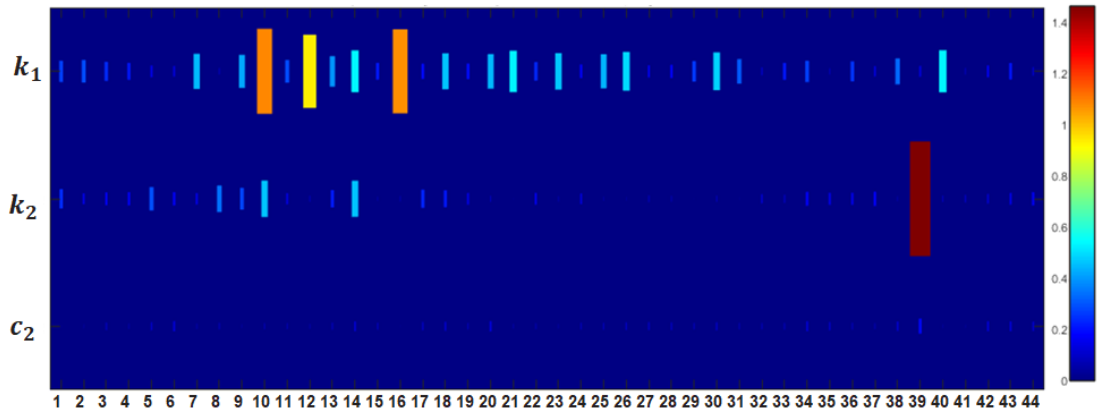

Fig. 2 Variance-based sensitivity indicator values visualized as a color matrix with parameters on the rows and outputs on the columns.

A NEURAL NETWORK MODELING

An alternative AI-based modeling approach is highlighted. The force is expressed as a function of the displacement x, the velocity v and the acceleration a: $F = g(x, v, a)$ and g is determined using an artificial neural network. The retained architecture is a multi layer perceptron composed of 3 inputs in the input layers: the displacement x, velocity v and acceleration a, 6 hidden layers, each with 30 neurons, and 1 output in the output layer: the force F. The Rectified Linear Unit (ReLU) function is selected as the activation function. Since the 30 data sets have a different number of values, their contents are interpolated to get 6 000 points in each one leading to 180 000 input values for the neural network. The whole set of input values is divided in the training data and the validation data in the proportion 80-20 and the Adam (adaptive moment estimator) optimizer is chosen. The resulting neural network model is validated using the original experimental data sets and the EEARTH score (Enhanced Error Assessment of Response Time Histories) metric, introduced in [11], is used to quantify the distance between the simulated and experimental forces as illustrated on Figure 3. The scores, above 0.949, demonstrate that the neural network model accurately captures the behavior of the component on the measured domain.

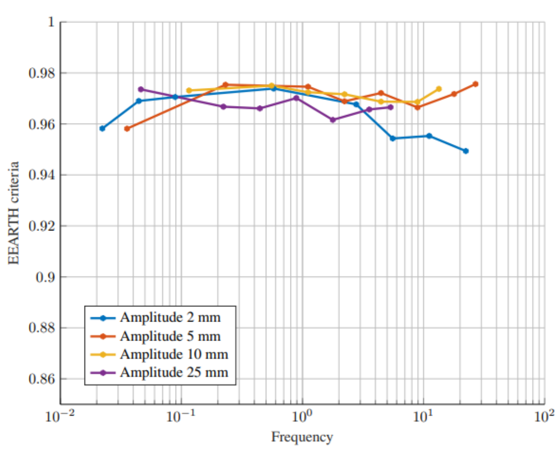

Fig. 3 Validation of the neural network with the computation of the EEARTH criteria for the 30 sets as a function of the excitation frequency.

CONCLUSION

A method for the search of the level of complexity required to validate a model in railway dynamics has been introduced. It relies on the determination of a decision-support indicator based on sensitivity analyses and it is applied to a yaw damper rheological model mounted on a motor bogie. A model developed using a multilayer perceptron neural network has been introduced that fully represents the component behavior within its training domain. The use of this type of black-box modeling disregarding any physical characteristics and time efficient is a good alternative when it comes to finding an acceptable compromise between the model complexity and the computational load.

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