Human performance modelling within rail decarbonisation simulation

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ABSTRACT

Rail simulation modelling can support decarbonisation, along with efficiency, capacity and safety. Modelling typically assumes perfect operator performance, or human performance is in some way stochastic (noise). In practice, human variability is rational while bounded by more general human performance characteristics (for example workload or fatigue). This study describes the foundations for more realistic human performance modelling within simulation. We describe two roles – driver and signaller – by which human performance can be embedded within systems models of rail operations. We describe the potential characteristics of those models including work in progress to show their impact. We also describe the functional mockup interface (FMI) standard and collaborative modelling paradigm that allows these models to be exported and embedded within other rail modelling efforts. In this way, there is a path for human factors to more accurately reflect the contribution and influence of human performance in rail simulation modelling efforts.

KEYWORDS

Rail human factors, simulation modelling, human performance, decarbonisation, functional mockup interface, FMI

Problem statement

Transport is a significant contributor to carbon emissions, and the railways offer an important pathway towards decarbonisation. Electrified rail offers lower carbon emissions in comparison to diesel rail, and substantial benefits in comparison to private car travel and road freight. Where full electrification is not viable, battery, hydrogen and hybrid technologies offer alternative strategies. Benefits can be amplified through timetable optimisation, energy efficient train driving and driver advisory systems, and technology such as regenerative braking. In the UK, this strategy underpins the contribution of railways to net carbon zero by 2050 (RSSB, 2019).

Rail systems simulation modelling is a common approach to understand rail performance. It plays an important role in design for hardware (rolling stock, infrastructure), as well as operational planning and optimisation, such as timetabling and train pathing. Simulation, therefore, plays a key role in planning for decarbonisation, be that the design of new components for energy efficient rolling stock (for example regenerative braking), the design of power supply to the rail network, or the design of power optimised operations, such as energy efficient timetables, or optimal design of discontinuous electrification. Examples of simulation modelling tools include Vision OSLO for power modelling, or RailSys for operational planning. However, modelling rarely takes into account human performance characteristics. Either human performance is not considered, or the human operator is assumed to perform perfectly (for example the driver always drives to the timetable), or a degree of noise is introduced to reflect variability in operator performance.

In practice, human performance characteristics are known to show variability that influences overall system performance (Powell and Palacin, 2015). In an operational railway the primary relevant roles are the driver and the signaller. For the driver, performance variability may come in response to driver strategy (for example training in defensive driving); interpretation of the rules; knowledge of ideal acceleration and coasting points; anticipation of signal states and known areas of congestion; or concerns around traction and adhesion issues due to weather or location. For the signaller, performance variability may come in response to peaks in demand; anticipation of congestion at regulation points and bottlenecks; or divided attention while dealing with other functions (for example user-worked crossings). It is important to note that these are not just performance decrements, or operators 'under-performing'. Operators are often optimising their performance with knowledge and experience of the wider system state or anticipated implications of their actions. In this sense, operator variability is rational, and describable, rather than stochastic and simply 'noisy'.

As well as this rational adaptation of behaviour, operational roles are also prone to more general limitations on human performance. For the signaller, this is primarily a concern of high workload impeding performance (Pickup et al., 2005), whereas for the driver this is often an issue of fatigue and decrements to vigilance (Filtness and Naweed, 2017). However, increased automation leading to greater periods of monitoring for the signaller, versus greater responsibilities for the driver at stations (driver only operation), or dealing with driving in congested conditions, means the extremes of high and low workload, and of fatigue, can affect both roles.

Methodology

The Digital Environment for Collaborative Intelligent De-carbonisation (DECIDe) project is applying a modelling approach from outside of rail – the multi-modelling paradigm (Fitzgerald et al., 2014) – to assess its feasibility for supporting rail decarbonisation. As part of this approach, we are integrating human performance within a simple rail systems model, shown in Figure 1. In the model, trains, which include a regenerative braking module, are controlled by a movement authority (a signalling system). As the train moves it draws power from a networked power supply (an overhead power system). This kind of power/rolling stock/timetable model is quite common in rail simulation to understand and optimise power performance. However, the model in Figure 1 covers human performance by the inclusion of a driver model who controls the train in response to the movement authority, and a signalling model who controls the movement authority subsystem.

The advantage of multi-modelling, a common approach in automotive and manufacturing sectors, is it allows the packaging of model components as functional mock-up units (FMUs, based on FMI [https://fmi-standard.org/]). These FMUs are interchangeable in a manner that enables rapid export and integration into different system models, without exposing intellectual property of proprietary models. One benefit of using this approach for human performance modelling is that, once written, a model of a human operator FMU (for example a train driver) can be exported and reused in other systems models. A second advantage is that each FMU can be implemented a number of times within a systems model and/or adapted to reflect different variations on performance (for example changing the FMU parameters to reflect expert rather than novice performance).

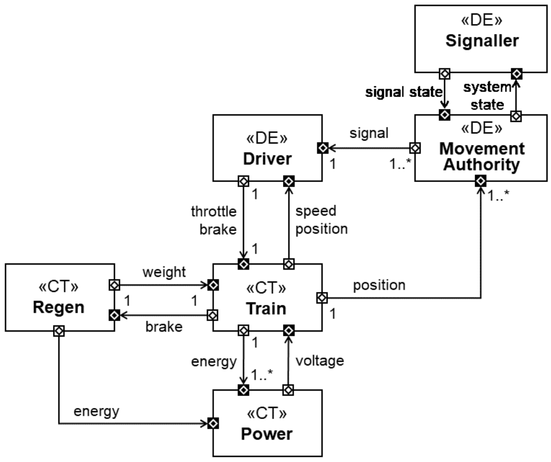

Figure 1: Simple rail system multi-model

Implementation

A driver model has been implemented, which includes a capacity to respond to signals, to apply power, to brake and (by lack of action) to coast. This is through the data interface between the driver FMU and the movement authority FMU. Additionally, power can be applied at different rates depending on the signal state (for example dropping to lower power approaching a cautionary aspect), coded as a parameter between the driver FMU and train FMUs specifying power application. Figure 2a-c shows the outputs of a simulation run over a 20km length of high-speed line, ending at a station stop. As the train proceeds along the track different driver actions occur in response to the signal state (reducing power at a cautionary aspect on approach to the station, and braking in response to a danger/stop aspect at the station) (2a). As a result, train speed slows initially and decreases rapidly (2b). Importantly for decarbonisation, driver performance influences power consumption, with power going back into the system from t=400 secs due to the regenerative braking (2c). Furthermore, two driver models and trains have been run in combination, this time for a lower speed metro system, to study cumulative effects including how different driving styles (aggressive use of power and brake, in comparison to more defensive driving) influence power performance, with two types of rolling stock: conventional, and lightweight with regenerative braking. These different energy consumption profiles are shown in Figure 3 (see also Pierce et al., 2019).

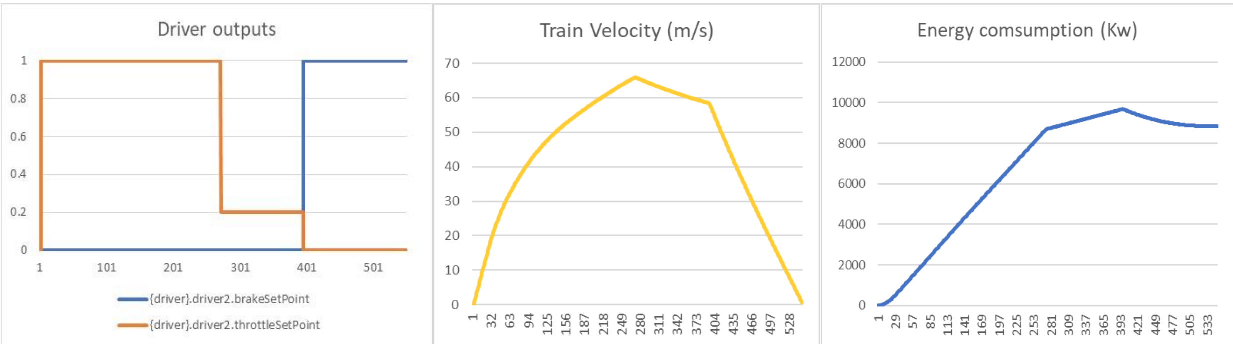

Figure 2a: driver model behaviour (brake and power); 2b: train velocity; 2c: power consumption

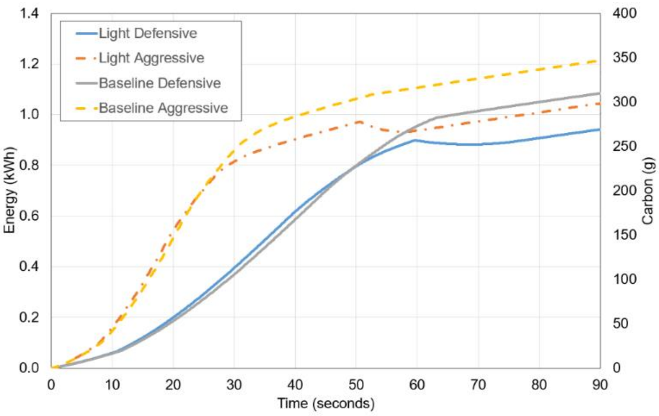

Figure 3: System energy consumption under different driver strategy (aggressive v defensive)

For the signaller model, an operator FMU has been exported from a similar control task – UAV control. The UAV operator FMU monitors multiple UAVs and performs interventions as the UAVs reach certain waypoints (Pierce et al., 2019). From a human performance standpoint, the operator model performs with lower efficiency at over 70% occupancy (high workload conditions) or below 30% occupancy (under-load conditions). As this model is an FMU, it is readily exportable to the rail model as an initial proxy to test the effects of signaller workload and situation awareness on over system performance. This has been achieved, therefore providing a baseline signaller performance model that both can set signals, and exhibit effects of high workload and under-load.

Conclusions

As the rail industry looks to use simulation modelling as part of its decarbonisation strategy, there is a need to make human aspects of modelling more realistic. For drivers, we have already integrated a basic driver model and shown how power savings are influenced by behaviour. For signallers we integrated a basic human performance model based on work in UAV control. As our model matures, we anticipate modelling more profound system effects (for example to show when a power-optimised timetable is truly achievable with realistic driver and signaller models). We are also looking to share our driver and signaller models with other decarbonisation modelling projects that are FMU-compliant. More accurate human performance modelling would also benefit the use of simulation for performance planning, capacity planning and understanding safety risk rates (for example occurrence of signal passed at danger). Finally, for both roles, we plan to extend models in a way that captures further performance characteristics, such as reaction time due to competency, or behaviour under other system conditions such as weather, or lighting conditions.

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