Multibody Modelling of Railway Vehicle Odometry Sensor Noise under Static and Dynamic Conditions

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Abstract
Railway signalling traditionally relies on simplified vehicle dynamic models, which often require extensive testing when applied to specific trains and tracks. However, advances in train speed and position estimation, and automatic train control systems (ATO) are challenging these simplifications. Modern odometry system integrates inertial measurement units (IMUs), wheel sensors, and GNSS, making its performance increasingly sensitive to the train's intrinsic dynamics.

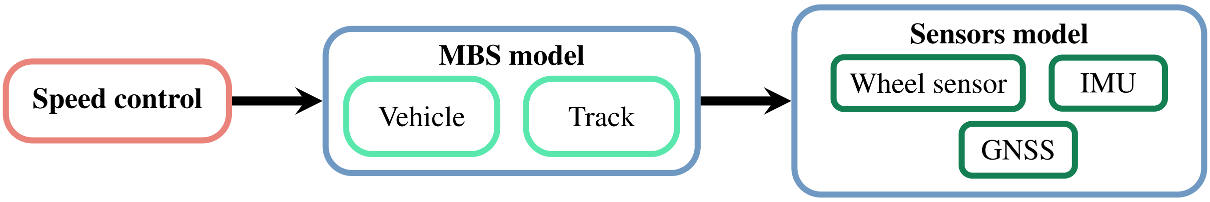

Figure 1: Schematic representation of the MBS model integrating the odometry system sensors models.

In the light of the above context, the current work aims to develop multibody models of railway systems to quantify and analyse the behaviour of odometry and Automatic Train operation systems. Such model has three main components (see Fig. 1): (i) the railway vehicle and track that were presented and discussed in [1], where the impact of considering the track curvature on the odometry system computation was highlighted, (ii) a realistic sensors model for odometry systems to provide measurements as if they had been taken in a real environment and (iii) a speed control module to follow a dedicated speed reference.
To achieve realistic outputs, the multibody framework must incorporate accurate representations of the sensors composing the odometry system with a particular attention to error modelling. Sensor signals are corrupted by errors of deterministic and stochastic natures. Stochastic errors, commonly referred to as noise, require stochastic models for their simulation. IMUs sensors suffer mainly from three types of stochastic errors [2, 3], each characterised by a specific Power Spectral Density (PSD):

- **Quantization noise**, introduced by the transformation from an analog into a digital signal. It has a constant PSD over the frequency range.
- **Angle/velocity random walk** has a thermo-mechanical nature for sensor using microelectromechanical systems (MEMS). It can be modelled as a white noise, i.e. with a constant PSD over the frequency range, on the sensor outputs (angular velocity and linear acceleration).
- **Bias instability** inherent to all electronic components and comes from irregularities within the conduction path. It is characterised by a PSD proportional to the inverse of the frequency. It is therefore also referred as a $1/f$ noise.

The IMU sensor is also subject to rate random walk noise, which is characterised by a PSD of the form $1/f^2$. Yet by experience, the latest is less impacting for IMU used in railway application.
Both the bias instability and the rate random walk noises are part of the so-called coloured noise family that gathered all stochastic processes with a power spectral density that evolves according to a $1/f^\alpha$ function. To generate real time coloured noise, an infinite impulse response (IIR) filter can be used [4].

When $\alpha = 1$ all the filter coefficients are non-zero, the $1/f$ noise is characterised by an infinite memory process. Nevertheless, it must be noted that all the coefficients have a significant effect on the computational cost as the simulation time increases. A truncation method can be used to reduce the number of coefficients while maintaining a satisfactory approximation of the $1/f$ noise PSD. Such approximation will result in a flat PSD of the generated noise for low frequencies (see Figure 2).

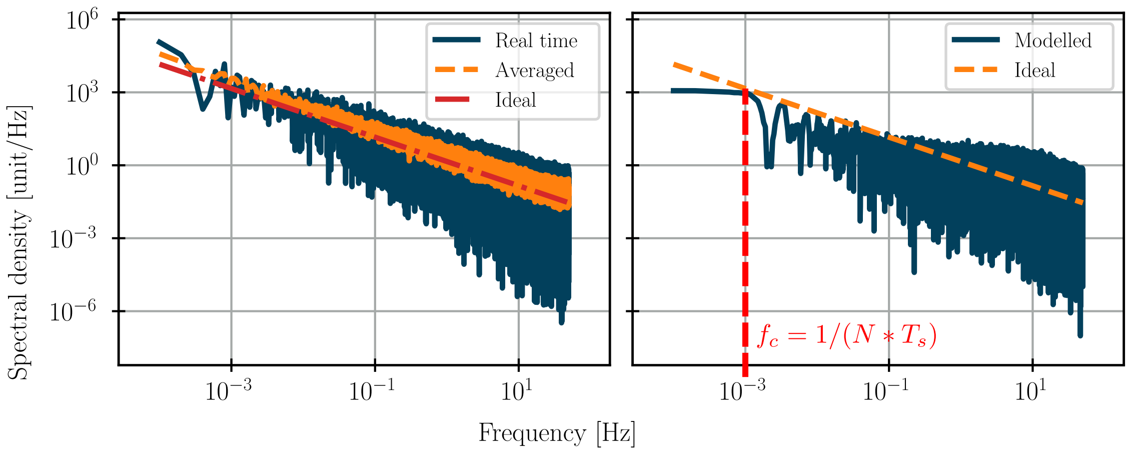

Figure 2: Power Spectral Density of real-time $1/f$ noise generated with an IRR filter. Left: convergence of the method with full filter coefficients. Right: impact of coefficients truncation ($N = 100\,000$ and $T_s = 1 \times 10^{-2}$ s).

One of the main challenges in automatic train control systems is ensuring accurate train stopping performance at the station. This requires precise knowledge of the train's stopping position. When the vehicle reaches a standstill, classical wheel-rail models tends to produce infinite creepages, as the wheelset velocity approaches zero. To address this limitation, we propose two modelling improvements:

1. A classical wheel-rail contact model is used at high and nominal speeds, while at low speed, it transition to a Coulomb-based friction model coupled with a hyperbolic tangent of the wheelset's angular speed. The transition between those two model is done progressively.

2. When a predefined speed threshold is reached, a viscoelastic model is superimposed on the friction model to ensure the vehicle comes to a complete stop.

Implementing those improvements allowed the train to reach a perfect standstill after few milliseconds of oscillation around the stopping position.

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