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Estimation of longitudinal velocity noise for rail wheelset adhesion and error level

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Abstract. The longitudinal velocity (forward speed) having significant importance in proper running of railway wheelset on track, depends greatly upon the adhesion ratio and creep analysis by implementation of suitable dynamic system on contamination. The wet track condition causes slip and slide of vehicle on railway tracking, whereas high speed may also increase slip and skidding to severe wear and deterioration of mechanical parts. The basic aim of this research is to design appropriate model aimed estimator that can be used to control railway vehicle forward velocity to avoid slip. For the filtration of disturbance procured during running of vehicle, the kalman filter is applied to estimate the actual signal on preferered samples of creep co-efficient for observing the applied attitude of noise. Thus error level is detected on higher and lower co-efficient of creep to analyze adhesion to avoid slip and sliding. The skidding is usually occurred due to higher forward speed owing to procured disturbance. This paper guides to minimize the noise and error based upon creep coefficient.

Keywords: longitudinal speed; adhesion; creep coefficient; kalman filter; tractive force

1. Introduction

The change in the contact condition can cause subsequent changes in the traction and braking responses of a rail vehicle, especially when the rail and wheel contact surfaces are contaminated leading to the well-known problem of low adhesion. The small adhesion shows severe confront to the tracking and braking control to keep away from wheel slip which can grounds the stern wearing of rail-wheel contacts, to enhance mechanical stress by influencing the steadiness and improves the incompatible traction problems in scheduling train. In some techniques, an adhesion coefficient is estimated by use of a disturbance observer (Shimizu *et al.* 2007, Hata *et al.* 2003, Ohishi *et al*. 2006).

One of the solutions of controlling hunting motion at higher speeds is to introduce independently rotating wheels at either ends of axle. Which is presented in (Goodall *et al.* 2000, it presents conservative wheelsets and un-conventional wheelsets. Also quasi-static oscillations with independently rotating wheels are analyzed and possibilities of control approaches to stabilizing railway wheelset without disturbing steady state systems are presented. This work is further

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carried out in (Goodall *et al*. 2001, Mei *et al.* 2003). As discussed earlier adhesion participates in the stability of railway vehicle as presented in which (Goodall *et al.* 2000) the factors that affect adhesion and consequences of low adhesion are presented. According to (Charles *et al.* 2006) the supreme velocity of railway vehicle is usually gained from axle except when all the axles are exaggerated in braking. The reliable sensors for insensitive environment are confined to the accuracy of measurement system.

Kalman filter is an estimation technique used extensively in vehicle dynamics applications because of its simplicity and accuracy. In (Charles *et al.* 2006) Kalman filter was used to estimate the adhesion condition on the rails. Estimation was carried out online during normal running. They showed that the different adhesion levels cause different responses in the railway vehicle, and that a Kalman filter can estimate wheelset forces well, to give an indication of the adhesion level (Charles *et al.* 2006).

In Polach (2005), the railway wheelset speed, acceleration and yaw rate signals are described without further simplifying model for the rail-wheel model. Usually off-line computation denotes the equal excellence of estimation can be obtained by comparing with a normal Kalman filter system (Wenhao Liao *et al.* 2014).

Nowadays the longitudinal train dynamical behaviour is almost totally controlled by braking on board subsystems, such as Wheel Slide Protection (WSP) devices. The study and the development of these systems are fundamental for the vehicle safety, especially at high speeds and under degraded adhesion conditions (Conti *et al.* 2014).

A wheel slide protection (WSP) system of a railway train has the role of reducing excessive wheel slide from brake applications in situations where wheel/rail adhesion is temporarily impaired. The WSP system is activated by a temporary reduction in braking force, and exploits available wheel/rail adhesion to a maximum and improves it by providing controlled wheel slide so that any increase in braking distance is kept to a minimum (Ho-Yeon Kim *et al*. 2014).

Hardware-in-the-loop simulation (HILS) for the WSP system can test various dangerous braking conditions which are not possible in actual train tests, and help to find appropriate parameters of the WSP system (Pugi *et al*. 2006). The mechanism of the WSP is complex and is related to highly nonlinear dynamics of the train. The mechanism of the WSP is complex and is related to highly nonlinear dynamics of the al train.

The disturbance effects on the system stability and on the torque estimation error in terms of speed error. The graphics show that the system is vigorous in terms of speed error and torque estimation error (Meli *et al.* 2014).

The Kalman fillter (KF) is process track current dormant signal like longitudinal velocity of railway vehicle. It is technique for estimating longitudinal speed scores when no former knowledge is accessible (Radionov *et al.* 2015). It is also used in combination with a maximum probability procedure called as predicting error decomposition to estimate parameters for dynamic and time series models (Shumway *et al.* 2004). Its central prediction algorithm is a state space model that genus the dynamic and measurement relations among latent states and manifest observations (Kuan Lu *et al.* 2014).

The simulation of degraded adhesion conditions is necessary to reproduce complex interactions that often arise among different mechatronic onboard systems and railway vehicle dynamics. Typical applications are the study and the simulation of WSP systems, anti-skid traction controls or odometry onboard subsystems. The numerical estimation of the adhesion coefficient from a set of data tests allowed a series of absolute slip/adhesion curves to be obtained (for each axle relative to different train speeds) (Malvezzi *et al*. 2012).

The slip and slide provide good traction and brake control functions and getting better the accuracy of the speed by the train odometer system. The Kalman and adaptive Fuzzy-Kalman filter algorithms are tested for getting better and correcting the train speed and train steering purposes. The algorithm has been evaluated by implementing on a real train positioning system by Mirabadi *et al.* (2009).

The kalman filter consists of two parts (1) projecting phase, where scoring prospect for the incoming period is produced (2) updating phase, where knowledge from mentioned parameters is integrated to update estimations from the projecting phase (Zarchan *et al*. 2000, Yishi *et al.* 2014).

The estimation is performed by an odometry algorithm increases the accuracy of the odometric estimation, in critical adhesion conditions, through sensor fusion techniques based on Kalman filter theory by melvezi *et al.* (2013). The odometric performance and two Kalman filters in terms of speed and travelled distance reliability are used for estimation of allowed speed profiles could estimate the train speed and position due to slip and slide phenomena.

In this paper, the longitudinal velocity of railway vehicle has ample influence upon wheelset dynamics for smooth running wheels on track. The certain limit of noise may cause slippage due to extreme limit of lateral velocity of railway wheelset. This lateral motion is usually directly proportional to the longitudinal velocity of railway vehicle. The kalman filter is implemented by estimating the actual parameters by measurements with estimated parameters to avoid disturbances caused by wheels. This estimator is used to check and reduce noise through application of various creep co efficient. Thus error percentage is detected to analyze the adhesion ratio depending upon creepage to avoid slippage.

This paper is structured by some sections to elaborate for title thoroughly. The railway wheelset dynamics is discussed through mathematical equation for longitudinal speed modeling in 1st section. In second section kalman filter is discussed for mathematical modeling of forward velocity. Third section contains simulation results comprising kalman filter and error estimation. In Section fourth, conclusions are presented.

2. Wheelset dynamics

A nonlinear model including the longitudinal velocity dynamics of the wheelset is presented in this section, which can be used as the simulation model for the wheelset. The railway wheelset

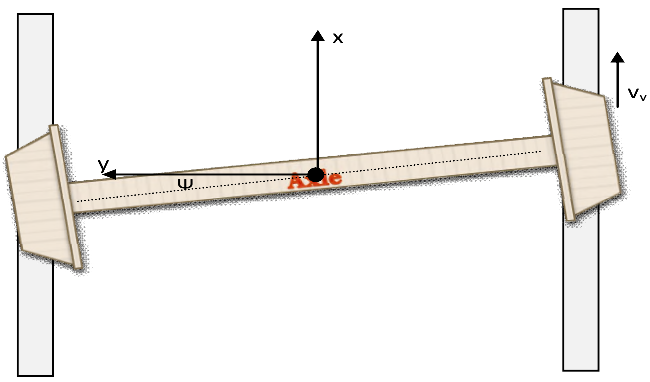

Fig. 1 Degree of freedom for railway wheelset

dynamic behaviors are dominated by the creeping forces produced at the rail-wheel contact surfaces. There are physically powerful connections among motions of railway wheelset based on the creeping forces at interface working in lateral and longitudinal paths (Soomro 2014). In Fig. 1, longitudinal and lateral directions are denoted by x, y and v_v as vehicle speed as under.
Creep relationship with speed of the wheels disposed laterally towards left follows as.

$$\lambda_x = \frac{v_w - v_x}{v_x} \quad \text{Where } v_w = r_o.\omega_w \text{ is wheel speed} \tag{1}$$

$$v_w = v_{wL} + v_{wR} \tag{2}$$

$$\lambda_{xL} = \frac{r_o\omega_{wL} - v_x}{v_x} + [\frac{L_g\dot{\psi}}{v_x} + \frac{\omega_{wL}\gamma(y - y_t)}{v_x}] \tag{3}$$

$$\lambda_{xR} = \frac{r_o\omega_{wR} - v_x}{v_x} - [\frac{L_g\dot{\psi}}{v_x} + \frac{\omega_{wR}\gamma(y - y_t)}{v_x}] \tag{4}$$

$$\therefore \lambda_x = \lambda_{xL} + \lambda_{xR} \tag{5}$$

Here L_g= gauge length of axle, $\dot{\psi}$ = spin velocity, y_t =noise, γ = coincity, , y = lateral motion.
λ_x =longitudinal creepage
The forward velocity of the wheelset for left and right wheel creep forces in longitudinal directions are

$$F_{xR} = f_{11}\lambda_{xR} \tag{6}$$

$$F_{xL} = f_{11}\lambda_{xL} \tag{7}$$

$$v_x = (\frac{r_o f_{11}}{M_v.v_{wR}})\omega_R + (\frac{r_o f_{11}}{M_v v_{wL}})\omega_L \tag{8}$$

The equations (6) and (7) are creep force of right and left wheels in forward directions. Whereas equation (8) represents combined velocity of right and left wheels for right and left wheels with 'f_{11}' as longitudinal creep co-efficient as ratio of creep force to creepage and 'M_v' as mass of vehicle. These dynamic equations are derived for comprehension, and kalman filter simulink to be used for simulation result after modification (Soomro 2014).

3. Kalman filter estimation implementation

The model-based techniques such as Kalman filters have been used successfully for the estimation of states as well as parameters**.** However, the use of a single estimator (through linearization or extension) has been found to be insufficient to tackle the complex problem because of the high level of nonlinearity and uncertainty (i.e. time varying) associated with the wheel-rail

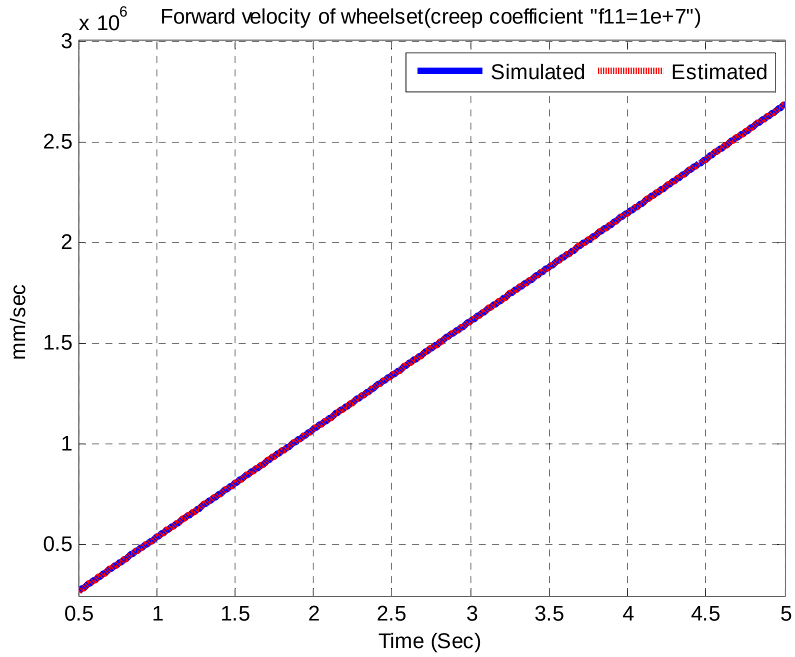

Fig. 2 Forward velocity wheelset at creep co-efficient of 10^7

contact mechanics.

The plan view model represents the dominant wheelset dynamic properties and is nearly always used for studies of this kind (Hsu 2010). Due to the presence of nonlinearities in the wheel–rail contact mechanics, the creep forces are linearlized. The distinct equation (9) is used to invent the Kalman filter (KF).

$$v_x(n+1) = v_x(n) + w_1(n) \tag{9}$$

The errors are considered as the process noise, denoted by

$$w_n = w_1(n) \tag{10}$$

the measurement equation for kalman filter is described as

$$y(n) = v_x(n) + v(n) \tag{11}$$

in equation (11), $v_{(n)}$ is the noise measurement. Thus state space model for longitudinal velocity is denoted by

$$X_{n+1} = \Phi X_n + W_n \tag{12}$$

$$y_n = HX_n + V_n \tag{13}$$

Where, X_n = $v_x(n)$ and X_{n+1} = v_x(n+1), Φ=1 are state factors at n and n+1 The covariance obtained by Kalman filter gain 'K_f' is calculated by simplifying the equations (10) and (11), thus Kalman filter is obtained by

$$X_{(n+1)} = (\Phi - K_f H) X_{(n)} + K_f . y_{(n)} \quad (14)$$

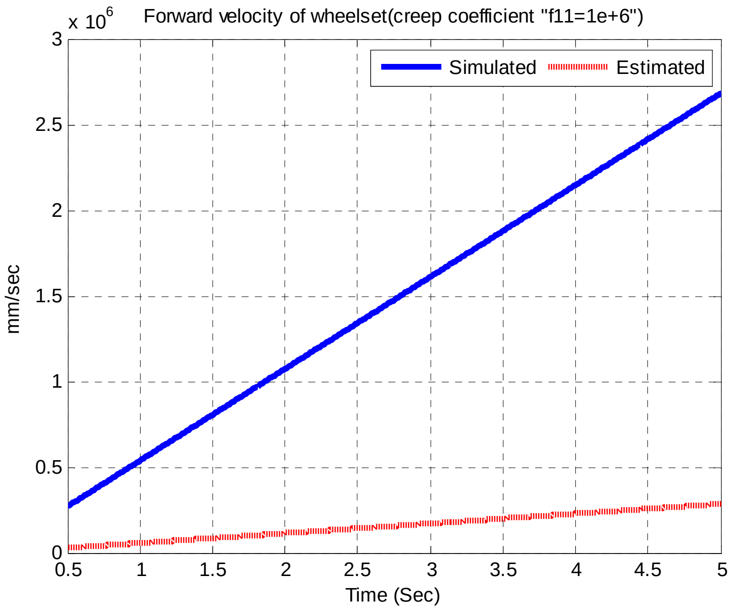

Fig. 3 Forward velocity wheelset at creep co-efficient of 10^6

4. Simulation results

Simulation results are classified in following two sections

4.1 kalman filter simulation

The longitudinal velocity of rail vehicle is estimated by kalman filter with actual parameters through different values of creep coefficient simulated and described as under.

In Fig. 2, the longitudinal speed for the railway wheelset has been simulated and displayed. Here forward velocity of the railway wheelset is testified by three different co-efficient of the creep versions to watch the performance of the railway wheelset as applied to other parameters. Here, when co-efficient of the creep is taken ad 10^7, we observe that forward velocity of the railway wheelset moves with velocity from 0 mm/sec initially to above 5×10^5 mm/sec finally in one second with time intervals from 0 sec up to 1 sec with increment of 0.1 seconds consisting upon actual and estimated parameters. Here actual values denoted by 'blue colour' moves along with the estimated values denoted by 'red colour' with inclined straight line.

This shows a lot variation in comparison to previous simulation, which means that when the co-efficient of the creep is reduced from $10^7$to 10^6 the estimation line goes apart from the actual parameter line. In Fig. 5 below, when the co-efficient of the creep is proposed as 10^5, we observe that forward velocity of the railway wheelset moves with velocity from 0 mm/sec initially to above

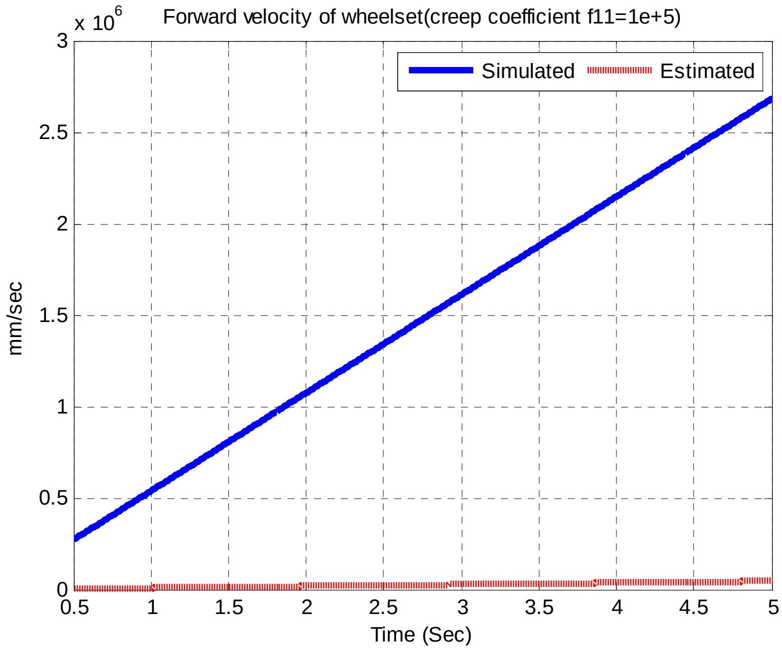

Fig. 4 Forward velocity wheelset at creep co-efficient 1e+5

5×10^5 mm/sec finally in one second with time intervals from 0.1 sec up to 1 sec with increment of 0.5 seconds for actual values denoted by 'blue colour' with inclined straight line. While the estimated parameter denoted by 'red colour' runs from 0 mm/sec in straight line with very minor above 0 to reach 0.1e+5 mm/sec in 1 seconds.

The results obtained from both diagrams 3 and 4, resemble with each except the image of the Fig. 2. This first portion shows that when the creep co-efficient is higher, then both actual and estimated parameters overlap each other, but whenever the co-efficient of the creep is decreased then both the actual and estimated values curves are separated from each other by significant at smaller distance from each other with different attitude.

4.2 Error estimation for forward velocity of wheelset

The railway train dynamic parameters are estimated to analyse the error ratio through high creep coefficient by blue line and low creep coefficient by red line. The higher co-efficient of creep is selected as 10^7 and lower coefficient is taken as 10^6 for estimation of error. The mentioned values of the high and low creep coefficient are applied to estimate the error ratio for forward velocity of wheelset of the train in Fig. 5 as under. Here blue line representing high creep co-efficient travels in straight direction from zero error value measurement scale. This means that there is no error in adhesion to occur slip shows maximum adhesion. While low creep coefficient denoted by blue line passes through 0 to 4.8×10^5 in vertical scale of error value with inclined line without major disturbances shows that imperfection and fluctuation of adhesion level. In Fig. 5, higher value for error estimation is denoted by 'e1' by creep coefficient and 'e2' is displayed by lower error estimation depending upon the coefficient of the creep with time scale in seconds horizontally.

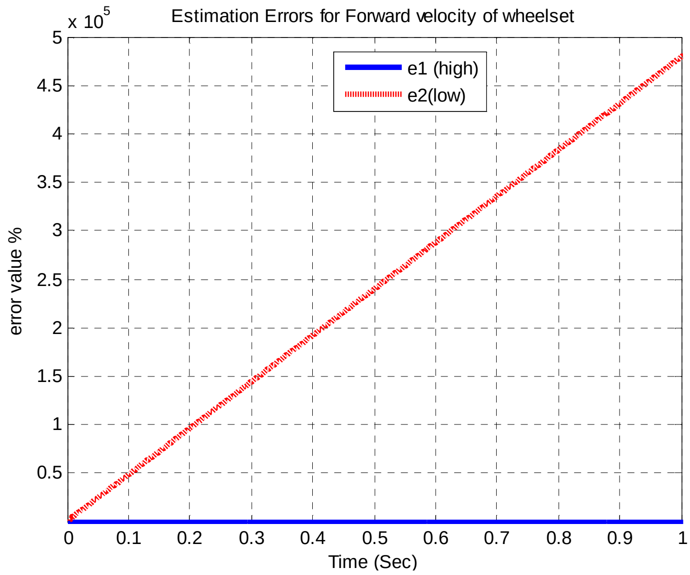

Fig. 5 Error estimation for forward velocity of wheelset

5. Conclusions

Vehicle speed also affects the adhesion level in contaminated conditions. The adhesion level which is the basic pretext of slip dependence raises with increase of creep yields stability for proper running of railway wheelset over track upon certain application of suitable longitudinal speed. The actual parameter values are estimated through certain measurement by using Kalman estimator to avoid the disturbance. It can be concluded that on decreasing the value of creep coefficient the actual and estimated parameters become apart and on enhancing creep coefficient they come nearer. Thus on higher value of creep coefficient, the error percentage becomes zero detects maximum level of adhesion to avoid slip on the forward speed of vehicle. This means that higher value of creep coefficient yields comparatively accurate consequences rather than lower value of it.

The railway wheelset has main two degrees of freedom comprising longitudinal and lateral directions. The longitudinal velocity is always considered in forward direction while lateral velocity is perpendicular to it. The dynamic combination of these two motions gets hunting due to un-stability of railway wheelset. This hunting is created by lateral oscillations due to disturbance on higher longitudinal speed. Thus strategy to control noise was presented.

The model performance is validated by means of simulating assumed different experimental data for forward speeds. The toning between experimental and simulated sliding is qualitatively fine. Since these physical quantities cannot be locally compared to each other because of the complexity and disorder of the system.

6. Future work

The whole simulation system has been implemented in the MATLAB -Simulink toolbox. An identification of the adhesion coefficient using a standard 'Neural network' procedure can be adapted for stable control of railway vehicle dynamic system.

An odometry system having sensors and ATP-ATC system can be used to estimate variations in the speed and the travelled distance of a railway vehicle. Since an error on the train track may be dangerous for braking system tracking orders.

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