Sindh Univ. Res. Jour. (Sci. Ser.) Vol. (45): 101-106 (2013)

SINDH UNIVERSITY RESEARCH JOURNAL (SCIENCE SERIES)

Design of Fuzzy Inference System for Condition Monitoring at Wheel-Rail Interface

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Received 13th September 2012 and Revised 08th January 2013

Abstract: Level of adhesion at wheel-rail interface plays an important role in the stable operation of a railway vehicle. Direct measurement of adhesion is not possible due to the presence of nonlinearities and unpredictable external contaminants. This paper presents an indirect technique to identify the level of adhesion at wheel-rail interface. The proposed identification technique uses the data recorded by inertial sensors mounted on the wheelset of the vehicle. A fuzzy inference system is used to monitor the data recorded by inertial sensors. Changes in the adhesion at wheel-rail interface are reflected in the recorded data. Which are interpreted by fuzzy inference into contact condition information.

Keywords: Fuzzy Logic**,** Wheel-Rail interface, Condition Monitoring, Adhesion

1. INTRODUCTION

The conventional railway vehicles maintenance and renewal activities rely on scheduled maintenance. The scheduled maintenance can sometime be unnecessary, resulting in extra cost and unnecessary disruption in train service, and some time the mechanical parts wear out before the scheduled maintenance is performed, resulting in faulty operations during the service which may also result in accidents. In modern railway vehicles sophisticated condition monitoring systems are installed to monitor the overall dynamic behaviour of the railway vehicle and notify critical conditions in order to take necessary action. A monitoring system that can predict or detect critical failures is a major contributor to system safety, which remains one of the most important attribute of railways compared with other transport modes.

Several condition monitoring techniques have been proposed to monitor the dynamics of the railway vehicles during operation. Some of the existing conditions monitoring techniques perform fault detection using advanced filtering, system identification and signal analysis methods (Goodall, 2006, Ward, 2011 and Ngigi, 2012). The model-based methodologies are preferred when there is no direct measurement of parameters but there is access to the relationship between the input and output signals . The model-based diagnostic techniques have been used to identify faults in dynamic systems through the evaluation of residuals (difference between estimation and measurements) (Hussain, 2009, Hussain, 2010).

This paper proposes a technique to monitor the condition of the track as the train travels down it. The idea is based on well known fact the dynamics of the railway vehicle are influenced with the changing adhesion levels. Direct measurement of available adhesion level is not yet possible due to presence of several nonlinearities and unpredictable external contaminations. There an indirect technique is proposed here which monitors the vehicle dynamics to identify the adhesion level. The proposed scheme uses only two sensors (a gyro sensor to measure yaw rate of the wheelset and an accelerometer for measuring lateral acceleration of the wheelset). A fuzzy inference system examines the residual signals and determines the adhesion level as the train travels through the track. This research is an extension of the work presented in (Hussain, 2009, Hussain, 2010, Hussain 2011 and Hussain, 2012). In previous work modelling and estimation techniques are presented. This paper covers the complete design of fuzzy inference system along with simulation results to show the potential of the proposed idea.

2. MODELLING OF SYSTEM DYNAMICS

A nonlinear wheelset model, given in equation (1), is used to simulate the behaviour of an actual wheelset.

$$\dot{x}(t) = f(x) + g(x)T_t \qquad (1)$$

Where state vector

$$x(t) = \begin{bmatrix} \omega_R & \omega_L & \theta_s & v & y_w & \psi_w & \dot{y}_w & \dot{\psi}_w \end{bmatrix}^T$$

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$$
f(x)=\begin{pmatrix}
-\frac{k_s}{I_R}\theta_s - C_s\omega_R + C_s\omega_L - \frac{r_o}{I_R}F_{xR} \\
\frac{k_s}{I_L}\theta_s + C_s\omega_R - C_s\omega_L - \frac{r_o}{I_L}F_{xL} \\
\omega_R - \omega_L \\
\frac{1}{M_v}F_{xR} + \frac{1}{M_v}F_{xL} \\
y_w \\
\psi_w \\
-\frac{1}{m_w}F_{yR} - -\frac{1}{m_w}F_{yL} + F_C \\
-\frac{k_w}{I_w}\psi + \frac{L_g}{I_w}F_{xR} - \frac{L_g}{I_w}F_{xL}
\end{pmatrix}
$$

and

$$
g(x)=\begin{pmatrix} \frac{1}{I_R} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}
$$

Simplifications presented in (Hussain 2009, Hussain 2010, Hussain 2011) are introduced in order design the Kalman filters and the resulting equations are given below.

$$\Delta\dot{x}(t) = A\Delta x(t) + G\Delta\dot{y}_t(t) \quad (2)$$

$$\Delta Z(t) = C\Delta x(t) + \Delta v(t) \quad (3)$$

where

$$\Delta x(t) = \left[\Delta\psi_w \quad \Delta\dot{y}_w \quad \Delta\dot{\psi}_w \quad \Delta y_t \quad \Delta y_w - \Delta y_t\right]^T$$

$$
A=\begin{bmatrix}
0 & 0 & 1 & 0 & 0 \\
\frac{2g_{22}}{m_w} & -\frac{2g_{22}}{vm_w} & 0 & 0 & 0 \\
-\frac{k_w}{I_w} & 0 & -\frac{2L_g^2 g_{11}}{vI_w} & 0 & -\frac{2L_g\gamma g_{11}}{r_o I_w} \\
0 & 0 & 0 & N & 0 \\
0 & 1 & 0 & 0 & 0
\end{bmatrix}
$$

$$
G=\begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ -1 \end{bmatrix} \quad
C=\begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ \frac{2g_{22}}{m_w} & -\frac{2g_{22}}{vm_w} & 0 & 0 & 0 \end{bmatrix}
$$

The creep curves shown in **(Fig. 1),** are used for the basis of the study. The Kalman filters are tuned to operate on saturation region of each creep curve. Simulations are run using different creep curves, shown in **(Fig. 2),** and the normalized rms values of the residuals with moving time window (Equation 4) are calculated, and some of the results are tabulated in **(Table-1)**.

Table-1: Residual values at different creep curves

Adhesion (μ%)	Filter-1	Filter-2	Filter-3	Filter-4
C_A (40%)	0.08	0.2	0.95	0.2-0.3
C_E (35%)	0.09	0.2	0.95	0.25-0.35
C_F (25%)	0.12	0.25	0.9	0.15-0.25
C_B (20%)	0.08	0.2	0.9	0.2-0.4
C_G (15%)	0.22	0.15	0.8	0.25-0.55
C_C (10%)	0.25	0.1	0.8	0.2-0.6
C_D (5%)	0.32	0.12	0. 8	0.6-0.65
C_H (3%)	0.5	0.4	0.12	0.72

$$
E_1 = \frac{\frac{1}{\Delta T}\int_{t-\Delta T}^{t}(E_1(t))^2 dt}{\sqrt{\frac{1}{\Delta T}\int_{t-\Delta T}^{t}(E_1(t))^2 dt + \frac{1}{\Delta T}\int_{t-\Delta T}^{t}(E_2(t))^2 dt + \ldots + \frac{1}{\Delta T}\int_{t-\Delta T}^{t}(E_n(t))^2 dt}} \quad (4)
$$

where E_1, E_2 and E_3 e.t.c are residuals of respective filter ΔT is the time window for which the rms value is calculated.

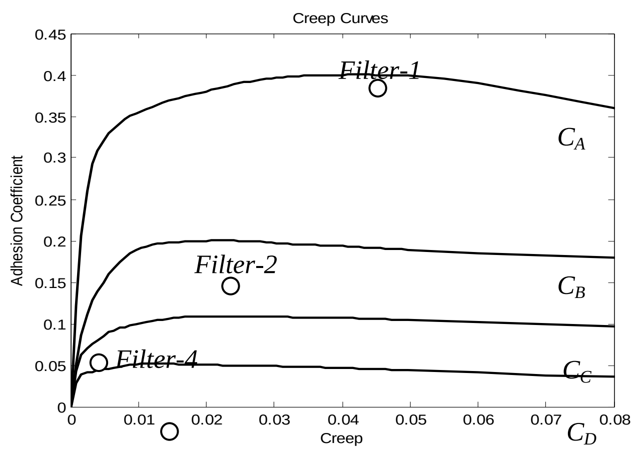

Fig.1 Creep curves used to design the Kalman filters

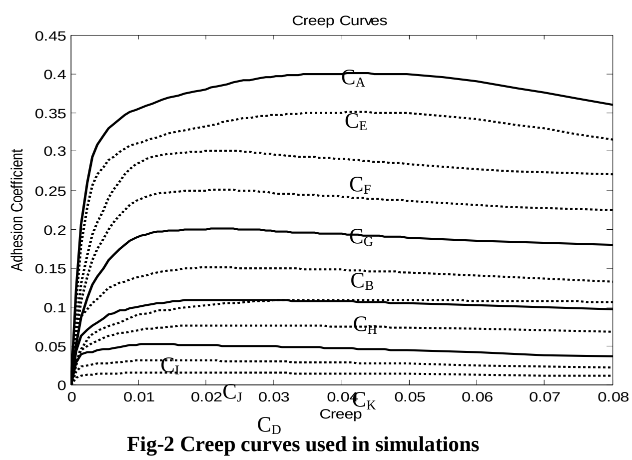

Fig-2 Creep curves used in simulations

3. DESIGN OF FUZZY INFERENCE SYSTEM

The basic idea of this research is that if wheelset operating point at the saturation region of a creep curve then the residual information together with the tractive torque can easily be used to determine the adhesion level. The fuzzy inference system (FIS) that analyzes the residuals and the tractive torque is shown in (Fig. 3). Two types of fuzzy inference systems can be implemented here: Mamdani-type and Sugeno-type. These two types of inference systems vary only in the way outputs are determined therefore the design of first two steps is same for either type of fuzzy inference systems. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant therefore not suitable for this application (Sugeno, 1985).

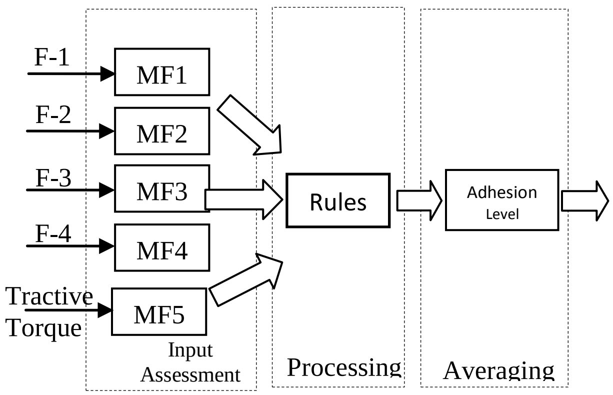

Fig.3 Fuzzy Inference System

After the thorough investigation of the residuals of all filters in different contact conditions the total span of the variation is divided into three categories, 'Low', 'Moderate' and 'High' as shown in figure-4 which provides a good imitative to design input membership functions.

Fig.5 shows the membership function of the residual of filter-1. The horizontal axis represents the normalized value of residual. The value of residual then determines the magnitude of participation of the input and the category it belongs to (e.g. 'High' if the residual value is 0.6 and the degree of membership is 1 and 'Moderate' and High' if the residual value is 0.35 and the degree of membership is 0.5 in this case). (Fig.5.6). shows the membership function of the residual of filter-2. The shape and the boundaries of the membership functions are fined tuned during simulations to ensure the best possible accuracy. The membership functions for the rest of the inputs are also designed using.

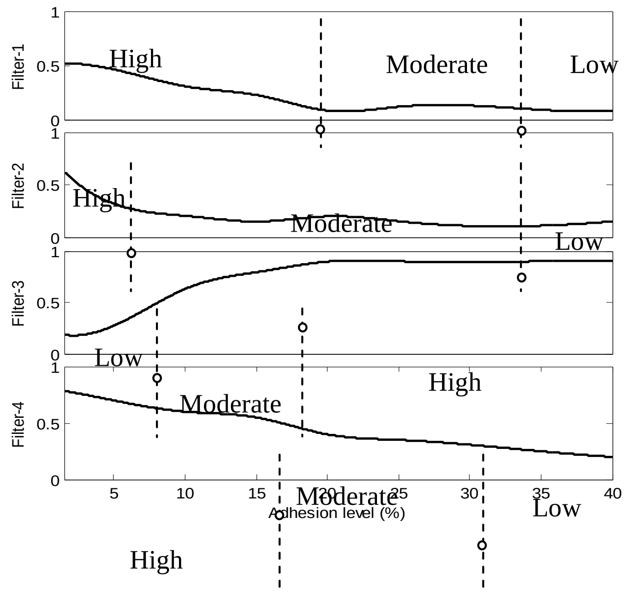

Fig.4. Variation of residual of filters

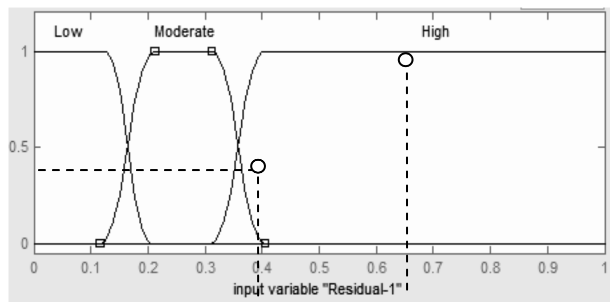

Fig.5. Membership function for the residual of filter-*1*

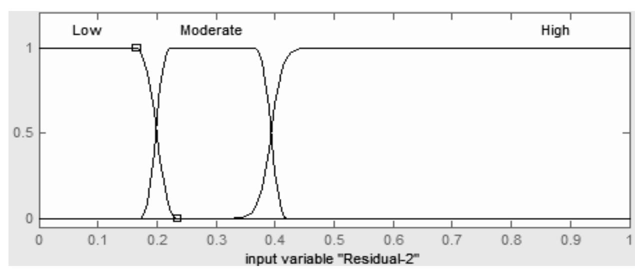

Fig.6. Membership function for the Residual of filter-2

Once all the inputs are scaled and combined they are processed according to the rules. Table-1 is used to derive the fuzzy logic rules. In fact in table-1 the numeric values are replaced by 'linguistic' variables and the new table is formed containing fuzzy logic rules **(Table-2).**

Table-2: Fuzzy Logic Rules

No	F-1	F-2	F-3	F-4	T	O/P
1	Low	Low High	High	Low	T8	μ≥40%
2	Low	Low High	High	Low Moderate	T7	40%≥μ≥20% μ≥40%
3	Low	Low Moderate	High	Low	T6	40%≥μ≥20% μ=20%
4	Low	Low Moderate	High	Low Moderate	T5	μ=20%
5	Low	Low	High	Low Moderate High	T4	20%≥μ≥10% μ=20%
6	Low Moderate	Low	Moderate High	Low Moderate High	T3	20%≥μ≥10%
7	Moderate	Low	High	Low Moderate High	T4	20%≥μ≥10% μ=20%
8	Moderate High	Low	Low Moderate	High	T2	μ=5%
9	Moderate	Low	Moderate High	High	T2	μ=5% 10%≥μ≥5%
10	High	Moderate High	Low	High	T1	μ<5% μ=5%
1	High	Moderate High	Low	High	To	μ<5%

In Mamdani-type inference the output membership functions is fuzzy set. After the aggregation process there is a fuzzy set for each output variable that needs defuzzification. In this case there is only one output variable (i.e. adhesion level) with fuzzy set shown in **(Fig. 7)**,. Output is determined by averaging the outcome of all the rules and final numeric output ranging from 0 to 100 is produced. For example the output 50 suggests the adhesion level is exactly between 20% and 10 % (15%) and the output 44 means the adhesion level is still between 20% and 10 % but more closer to 20% (i.e. nearly 18%). Similarly a numeric output 55 suggests that the adhesion level is exactly between 20% and 10 % but more closer to 10% (nearly 12%).

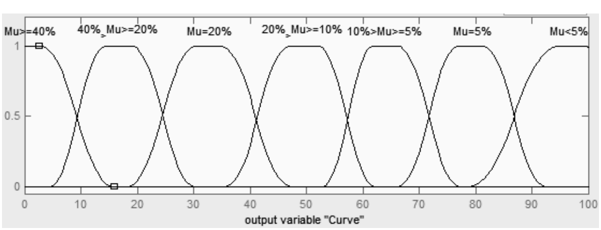

Fig.7. Output Membership function

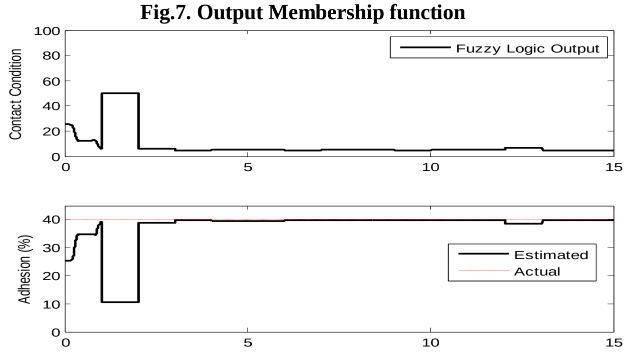

Fig.8. Simulation carried out using creep Curve C_A

4. SIMULATION RESULTS

(Fig. 8), shows the output of the fuzzy inference system when the system is operated on creep curve C_A. The system takes approximately two seconds to react and produce correct output. The delay in this case is 2 seconds which is the result of the time consumed by the PI to control the tractive torque steadily and 1 second is required to calculate the windowed rms of residuals. After 2 seconds the output fuzzy logic system is steady and the estimated adhesion level is almost equal to the actual adhesion level.

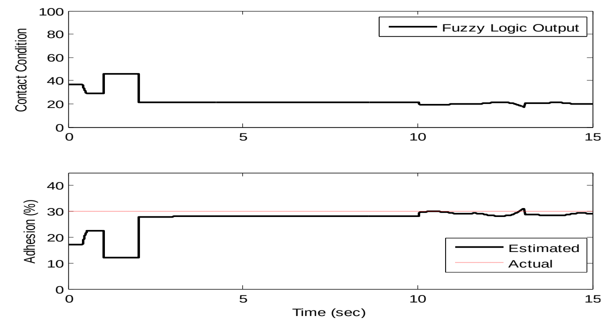

Fig.9. Simulation carried out using creep Curve C_C

(Fig. 9), shows the result obtained by simulating the Simulink model using creep curve C_C. Again the steady output is produced after a delay of approximately 2 seconds. It is worth noticing here that almost half of the delay is caused by the PI controller which during simulation gradually increases the tractive torque from zero until it reaches to saturation point and try to hold the operating point for sufficient amount of time in order to analyze the residuals. In practice while the wheelset already be in motion the amount of delay would not be that much. After the expected delay the estimated adhesion level is approximately equal to the actual adhesion level. The difference in the actual output and the estimated output is caused by several reasons that include inaccuracy in fuzzy interpretation. Similarly **(Fig.10).**shows the result of the simulation when the wheelset is operated on creep curve C_F.

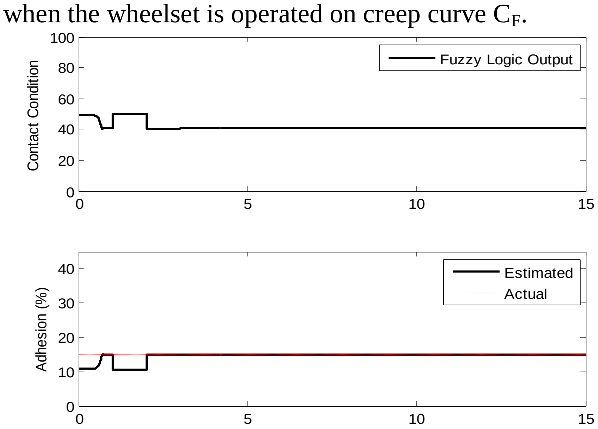

Fig.10. Simulation carried out using creep Curve C_F

(Fig.11).shows the simulation result when the system is operated on creep curve C_L. The estimated output is again equal to the actual adhesion level but this time a delay of 5 seconds is observed. This is because it is a low adhesion condition with adhesion level 3% therefore the tractive torque adjustment is comparatively slow otherwise the operating point jumps to unstable region of the curve. In other words the integral gain is kept low which increases the settling time of the PI controller hence the more delay. With high integral gain the operating point overshoots beyond saturation region

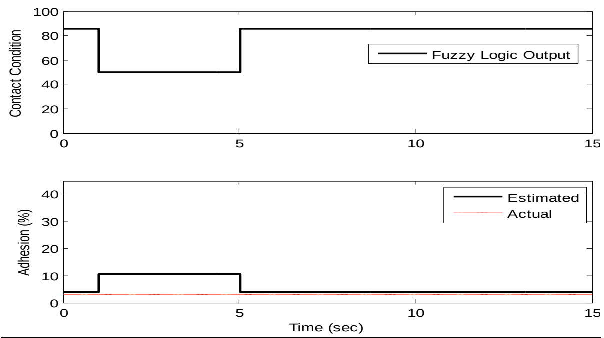

Fig.11. Simulation carried out using creep Curve C_L

5. CONCLUSIONS AND FURTHER WORK

Simulation results show that the fuzzy logic system is able to pick up any changes at the wheel-rail interface. Although the simulation are carried out using only single wheelset model but the accuracy in the results shows the potential of the proposed idea. Number of measures can be taken to further improve this system before implementation. Some of which include improvement in the simulation conditions. Such as, tractive effort can be controlled in a better and smooth way in order to keep the operating point at desired location on the creep curve, which will eliminate small fluctuation in fuzzy logic output. PI controller that is used to control the tractive torque takes some times more than two seconds to reach at desired value which introduces delays at the output of the fuzzy inference system. If tractive torque is controlled by some other means this delay can be minimized. After successful simulation the proposed system can be put into the practice by using a suitable implementation method.

Appendix: List of Symbols

ω_L, ω_R Left and right wheel angular velocities
v Vehicle Speed
M_v, m_w Mass of vehicle and mass of wheelset
I_R, I_L Moment of inertia of right wheel, left wheel
I_w Yaw moment of inertia
ψ Yaw Motion
y_w Lateral Motion
F_L, F_R Left and right wheel Creep forces
F_{xL}, F_{xR} Left and right wheel Creep forces in longitudinal direction
F_{yL}, F_{yR} Left and right wheel Creep forces in lateral direction
C_s, K_s Material damping and stiffness of axle
K_w Yaw Stiffness
θ_s Torsional Angle
F_c Centrifugal Force
L_g Track half gauge
r_o Wheel radius
g_{11}, g_{22} Linearized creep force coefficients

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