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“New methods for the condition monitoring of level crossings”

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New methods for the condition monitoring of level crossings

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Level crossings represent a high risk for railway systems. This paper demonstrates the potential to improve maintenance management through the use of intelligent condition monitoring coupled with reliability centred maintenance (RCM). RCM combines advanced electronics, control, computing and communication technologies to address the multiple objectives of cost effectiveness, improved quality, reliability and services. RCM collects digital and analogue signals utilising distributed transducers connected to either point-to-point or digital bus communication links. Assets in many industries use data logging capable of providing post-failure diagnostic support, but to date little use has been made of combined qualitative and quantitative fault detection techniques. The research takes the hydraulic railway level crossing barrier (LCB) system as a case study and develops a generic strategy for failure analysis, data acquisition and incipient fault detection. For each barrier the hydraulic characteristics, the motor's current and voltage, hydraulic pressure and the barrier's position are acquired. In order to acquire the data at a central point efficiently, without errors, a distributed single-cable Fieldbus is utilised. This allows the connection of all sensors through the project's proprietary communication nodes to a high-speed bus. The system developed in this paper for the condition monitoring described above detects faults by means of comparing what can be considered a 'normal' or 'expected' shape of a signal with respect to the actual shape observed as new data become available. ARIMA (autoregressive integrated moving average) models were employed for detecting faults. The statistical tests known as Jarque–Bera and Ljung–Box have been considered for testing the model.

Keywords: condition monitoring; railway; maintenance; level crossing; ARIMA; Jarque–Bera; Ljung–box

1. Introduction

Level crossings are safety critical elements of a railway. They define a region where road vehicles or pedestrians can occupy the space usually occupied by a railway vehicle, contributing 35% of the overall risk of train accidents. Ninety-five per cent of level crossing-related accidents are caused by misuse by crossing users in the United Kingdom (UK). The most common risks are of collision between a train and a road vehicle or pedestrian, and the derailment of the train. Approximately 6% of the overall railway risk is caused by level crossing, divided into: 57% pedestrians being struck; 35% from collisions between trains and road vehicles; and, 8% from pedestrians stuck/trapped by crossing elements (Rail Safety and Standards Board 2006).

For a level crossing barrier, the normal throw is defined as the movement from the lowered to the raised position through the force supplied by an electro-hydraulic power pack. The reverse throw, from the raised to the lowered position, is driven by gravity, with the barrier effectively free-falling to the lowered position.

The most commonly used level crossing barrier in the UK is the BR843 type. A full fault detection algorithm was developed of a condition monitoring system for BR843

to improve its reliability, availability, maintainability and safety. The algorithm consists of the following steps:

- (1) Determine the historical data to use. In a later case study the last 300 free-from-fault movements of the point mechanism at each point in time are used to estimate a model. One sophisticated modelling methodology implemented here to forecast the signal is the ARIMA (autoregressive integrated moving average) or Box–Jenkins methodology (see below) (Box, Jenkins, and Reinsel 1994).
- (2) A forecast of the length of time of the next movement is produced by means of an ARIMA model, together with a forecast interval that is fixed as the number of times the standard deviation of the forecasts. This interval is fixed empirically here to produce the best performance of the algorithm and would be different from one mechanism to another.
- (3) As new signal data points of the next movement become available, the time length has to be detected and compared with the forecast interval in the previous step. It may be the case that the time length is too short and falls out of the interval in Step 2.

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In that case a fault is detected. On the other hand, the length could be longer than the forecast interval. This also indicates a fault. If the time length falls within the forecast interval, the mechanism is considered to be working properly.

- (4) The historical data-set is updated. If a fault is detected the historical data to perform step 1 for the next movement is the same as before. If no fault is detected, then this last movement is incorporated into the historical data next time it is going to start from Step 1 and the first movement is dropped off the sample. In this way, the time-varying properties of the system, if any, are always taken into account in the algorithm.

The paper presents a real case study on which the method is demonstrated as to how it works. The method may seem too complex for the case study analysed, but it is general enough to be applied to much more complicated cases. In this sense, this paper opens up a door to further research on other data that may be explored.

2. Level crossing

The case study was developed in collaboration with Rail-track (now Network Rail), GTRM (now Carillion) and Jarvis. The fault detection and diagnosis algorithms outlined in this paper were tested on live sites.

The equipment illustrated in Figure 1 is typical of a manually controlled barrier (MCB) BR843 installation. The automatic half barrier (AHB) is similar in construction, but without a skirt and supplementary support components. The principal components of a BR843 barrier are (Nock 1980; Leach 1991):

Figure 1. Level crossing barrier.

- An electro-hydraulically operated BR985 power unit in a steel weatherproof cabinet bolted to a concrete base, that accommodates the electrical controls, as well as a means of manual operation.
- Counterweighted sidearms, mounted on the machine pivot shaft. A variety of balance weights may be used, either singly or in combination, to ensure that sufficient ‘out-of-balance’ force remains, due to the boom (and skirt where fitted), to allow the barrier to descend against the maximum wind speed (46 ms^{-1} - AHB; 30 ms^{-1} - MCB).
- The barrier boom itself is mounted on one sidearm. The shortest standard boom length (measured from pivot to tip) is 3.6 m and the longest is 9.1 m, with intermediate variations in steps of 500 mm.
- A support member, mounted to stiffen the boom in the horizontal plane, and a straining wire, to stiffen the boom in the vertical plane. The support member and straining wire are only provided for barriers over 6.6 m long (i.e. MCB).

The arrangements are such that the hydraulic pump unit drives the boom to its raised position where it is held by an energised solenoid valve. This, when de-energised, permits the barrier to return to its horizontal position by gravity. Re-energisation of the solenoid valve during the descent of the barrier will immediately stop the descent. The principal features of the hydraulic circuit (Figure 2) are:

- (1) An electrically driven pump to deliver oil under pressure to extend the actuator and thus raise the barrier. The motor driving the pump is energised through contacts remote from the unit.
- (2) A normally open solenoid valve which, when energised, is closed to prevent the flow of oil from the actuator and thus maintains the barrier in its raised position.
- (3) A pressure-compensated adjustable flow regulator to control the rate of flow of oil from the actuator, and thus the speed of descent of the barrier. The arrangements are such that further control is exercised over the last $10\text{--}15^\circ$ of descent, to bring the barrier gently to rest.
- (4) A means of selecting ‘auto’ or ‘manual’ mode of operation, for AHBs and MCBs, respectively, the unit being locked and sealed in the selected mode.
- (5) A hand lever operated pump system for local operation of the barrier, which can be operated at will to override power operation. The lever is extended for hand pumping, and only permits the access door to be closed and power operation to be resumed when it has been retracted and stowed in its out-of-use position. The lever has a ‘hold’ position that prevents the barrier from lowering and is capable of arresting its movement at any point while in motion.

Figure 2. BR985 hydraulic circuit.

- (6) An oil reservoir forms an integral assembly with the actuator. Suitable oil filtration arrangements are provided to prevent foreign particles from entering the hydraulic circuit. Pressure relief arrangements to prevent overloads damaging the system or the motor driving the pump are also provided.
- (7) The hydraulic circuit is a self-contained system such that the power unit may be installed and removed from the barrier machine housing without making any hydraulic disconnections. As far as practicable, elements of the hydraulic system circuit are contained in a suitable manifold to minimise the number of hydraulic connections and the consequential risk of leaking.
- (8) The shock absorber plunger prevents the barrier from oscillating when it comes to rest in the raised position. When the shock absorber plunger is compressed, pressure is maintained on the seals within the hydraulic power unit. This pressure is necessary to prevent the seals from relaxing, thereby preventing hydraulic oil leaking past the seals and allowing the barrier to fall.

The pressurised oil under the jack piston is trapped by the solenoid valve whose coil is re-energised to lower the barrier. On removal of current from the coil, the solenoid opens and the trapped oil escapes back into the tank, in turn lowering the barrier. Before reaching the tank the oil passes through an automatic speed control valve and the stop valve, as shown in Figure 2. The jack is also provided with a damper that decelerates the lowering of the barrier over the final 10° to restrict bounce. Table 1 shows the typical operating characteristics of the pump unit.

Based on the grouping of failure modes and root causes it was decided to use the following sensors: electric motor voltage, electric motor current, hydraulic pressure and

Table 1. Typical operating characteristics for a BR985 pump unit.

Operating characteristic	Value
Operating voltage (volts)	22–30
Motor current – max. (Amps)	29
Motor current – working (Amps)	15
Relief pressure setting (bars)	145
Average working pressure (bars)	34.5

Figure 3. Typical hydraulic pressure and displacement profiles during rising.

rotary position. A major sensor specification such as frequency responses and sensitivity is done in reference (Nash and Roberts 1999).

Using conventional data acquisition systems a large amount of cabling would have been required to centralise the sensor signals for processing. The long cabling runs also invariably allow the analogue signals being transmitted to be subjected to high levels of electrical noise. To avoid these problems a digital fieldbus communication system was utilised which significantly reduces the amount of cabling and has high EMC (electro-magnetic compatibility) noise immunity.

Data were collected from a number of test sites using non-invasive transducers and also from a level crossing test rig situated in the University of Birmingham (UK).

Figure 3 shows a typical raising hydraulic pressure and rotary displacement profiles taken from a 5.6-m barrier at Langley Green MCB near Dudley. Examining the hydraulic pressure trace, it can be seen that the pressure transducer mounted at the gauge point (see Figure 2) records a significant peak of oil pressure as the electric motor is initiated. At the end of the throw, the oil pressure rises as the barrier approaches the vertical position where the solenoid valve is energised. During the movement the rotary velocity is approximately constant ($\sim 0.3 \text{ rad s}^{-1}$). A typical pump motor current and rotary displacement profiles have a shape similar to the signal shows in Figure 3 but with a higher second peak. The initial peak of approximately 55 bars (30 A in the current signal of the pump motor) in the current waveform is associated with the characteristics of the permanent magnet motor. The second peak of around 75 bars (25 A in the current signal of the pump motor) is produced as the hydraulic pressure in the system becomes sufficient to begin the lifting of the barrier. The barrier is lowered by de-energising the solenoid and allowing the boom to free

fall. In the final stages of the throw the effect of the damper can be observed as the boom comes to rest. Lowering of the barrier is slightly slower than the raising with an average speed of 0.25 rad s^{-1} .

A rapidly lowering boom could cause a serious accident if it were to fall on to a moving vehicle. As the fault had the potential to cause a safety risk to members of the public, the faulty barrier pack was removed from the crossing and taken to the Technical Investigation Centre (TIC) in Crewe for further inspection.

3. Detection of faults in point mechanisms

Several signals related to the level crossing mechanism were registered (electric motor voltage and current, hydraulic pressure and rotary position), but examining voltage (measured in volt units) is enough to detect faults in the mechanism selected. Figure 4 shows the typical shape of the voltage signals registered where the long inactivity periods have been eliminated in order to show more clearly the typical profile of the signals.

Such a shape is rather simple, as expected. It consists of a rapid rise in voltage up to approximately 23 volts, followed by a period where it remains approximately constant, then a rapid fall. Some variations are expected with many variables, such as the wear of the mechanism, environmental variables, and so on. The time that the system takes to generate the upwards and downwards movements is the key point in the detection algorithm, as it will be shown below.

The authors have analysed the shape of the signals mentioned above (Tobias, Garcia Marquez, and Roberts 2010), employing the methods described in references Pedregal, Garca, and Schmid (2004), Garca, Weston, and Roberts (2007), Garca and Schmid (2007) and Nash and Roberts (1999), but they could not detect any fault except the faults found in this paper studying the length time signals. In order to simplify the method for detecting and diagnosing faults in level crossing barriers, the authors have employed only the method that analyses the time length of the movement.

Figure 4. Examples of voltage signals registered appended one after another.

Figure 5. Time (in seconds) the system takes to produce a full movement.

model. The most important validation tests are the absence of serial correlation and the Gaussianity of the perturbational noise e_t (Box et al. 1994). Optimal forecasts are then computed recursively on the basis of the actual data and the estimates of the model parameters, once the model passes a validation process. Based on the Gaussianity assumption for the perturbation, confidence bands for the forecasts may be estimated.

One important fact is that the signal z_t on which all the ARIMA methodology is applied should be stationary in mean and variance. A simple analysis of the signals in Figure 5 reveals that for such data, simple differences solve the problem, i.e. calling z_t^* the signal in Figure 5, stationarity is produced by taking $z_t = z_t^* - z_{t-1}^*$.

In order to make the procedure completely automatic, we have taken advantage of the automatic identification routines implemented in the software TRAMO (Time Series Regression with ARIMA noise, Missing observations and Outliers) (Caporello and Maravall 2004). This software incorporates programs for automatic identification of ARIMA models with the intervention of outliers and estimation of models altogether. The basic objective function on which the models are selected is the Bayesian Information Criterion, which improves as the fit of the model is better but is penalised by the number of parameters. This piece of software is very convenient in this case, because it produces an automatic identification of ARIMA models in fractions of a second, i.e. the model structure automatically is updated and estimated depending on the data observed, without any additional human intervention.

4. Results

There is one detail in the system that must be fixed by experimentation on just empirical grounds, namely the alarm limit in terms of standard deviation of signal z_t . The final setting for this case study is four times the standard deviation, because this is a value that produces the best discrimination between faulty and non-faulty movements. Other values should be specified for other device maintenance.

One of the most important points in the methodology is the automatic identification procedure implemented in TRAMO, which provides different models, depending on the forecast origin, implying that the length of the movements have time-varying stochastic properties. The method includes automatic identification of model orders, combined with automatic detection of outliers and several automatic tests performed previous to the ARIMA modelling (like logarithmic scale pretest or the necessity of a constant in the model, see Caporello and Maravall 2004). This complex procedure makes sure that the best possible model is always applied to the data at each forecasting point. Most of the time the model automatically identified is ARIMA (0, 1, 1). One typical estimation was

$$z_t - z_{t-1} = e_t - 0.88e_{t-1}.$$

The length of time for which the voltage exceeds X volts during an upwards movement is shown in Figure 5 for all the recorded movements. All but one of the movements lies in the interval of 5.8 to 8 seconds. The one exception happens due to a fault in the mechanism (just 0.7 seconds). It should be pointed out that the signal is full of preventive replacements, due to the fact that the data come from a working cross level device on a real train track.

Modelling and forecasting this signal into the future constitutes the basis of the fault detection system implemented, since forecast values far from a given confidence interval would be an indication of a failure, in a similar way as it is usually considered in other areas of maintenance, like vibration analysis (Christer, Wang, and Sharp 1997; Pedregal and Carnero 2006 and references therein). Even probabilities of failure could be calculated on the basis of such a forecasting model (Garca and Pedregal 2007; Garca et al. 2007; Garca and Schmid 2007).

One sophisticated modelling methodology implemented here to forecast the signal shown in Figure 5 is the well-known ARIMA (autoregressive integrated moving average) or the Box-Jenkins methodology. ARIMA models are usually typified by the model orders, p , q , and the number of differences necessary for mean stationarity transformation, d . The general usual nomenclature is ARIMA (p , d , q).

A general ARIMA model is of the form

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \dots + \phi_p z_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots + \theta_q e_{t-q}, \quad (1)$$

where z_t is the time series shown in Figure 5; e_t is white noise, i.e. purely random signal with no serial correlation and constant variance σ^2 ; and ϕ_i ($i = 1, 2, \dots, p$) and θ_j ($j = 1, 2, \dots, q$) are unknown parameters.

One key issue in ARIMA modelling is the identification of model orders p and q . In this respect, the Simple and Partial Autocorrelation functions are the tools mostly used for such tasks. The parameters as well as the noise variance have to be estimated by Maximum Likelihood. Validation tests are then carried out on the residuals of the

Table 2. Results for the first and second sample (test P-values in parentheses).

	Jarque–Bera	Ljung–Box Q(1)	Ljung–Box Q(4)	Ljung–Box Q(8)
First sample	1.79 (0.41)	0.62 (0.42)	1.75 (0.78)	2.68 (0.95)
Second sample	5.46 (0.06)	1.62 (0.21)	6.01 (0.19)	11.02 (0.20)

The same procedure applied in the middle of the sample produced an ARIMA(3, 1, 1). The estimation was

$$z_t - z_{t-1} = 0.19(z_{t-1} - z_{t-2}) + 0.25(z_{t-2} - z_{t-3}) \\ + 0.18(z_{t-3} - z_{t-4}) + e_t - 0.56e_{t-1}.$$

350 All the coefficients are statistically significant and the residuals corroborate that the model is correct. Two of the most used tests are the Ljung–Box test of serial correlation (Ljung and Box 1978), and the Bera–Jarque normality test (Jarque and Bera 1980).

355 The autocorrelation Ljung–Box test is based on the squares of the first k autocorrelation coefficients (r_j) on a set of T observations. The statistic is

$$Q(k) = T(T+2) \sum_{j=1}^k \frac{r_j^2}{T-j},$$

with a chi-squared distribution with k degrees of freedom. The null hypothesis is that the residuals are not correlated, 360 i.e. the ARIMA model has captured all the temporal dependence in the data. This happens whenever the statistic $Q(k)$ estimated on a given sample is smaller than the corresponding value on the chi-squared distribution with k degrees of freedom for a given significance level (usually 5%), i.e. the 365 P-value in Table 2 below is greater than 5% (0.05).

The Bera–Jarque normality test statistic is

$$BJ = T \left(\frac{A^2}{6} + \frac{(K-3)^2}{24} \right),$$

where A and K are the skewness and kurtosis coefficients, respectively. Its distribution under the null hypothesis is chi-squared with two degrees of freedom. The null hypothesis 370 is that the residuals are Gaussian and such hypothesis is not rejected at 95% of the confidence level whenever the value BJ is small enough to leave a probability greater than 5% (the P-value) on the right-hand side of a chi-squared distribution with two degrees of freedom.

375 Table 2 shows the results obtained for the first and second samples taking into account the Jarque–Bera and Ljung–Box Q(1, 4, 8).

380 It is clear that there are no problems of Gaussianity and serial correlation in any of the samples, since all the tests imply that it is not possible to reject the null hypothesis

of either tests, in many cases with an ample margin of confidence, judging by their P-values.

The ARIMA models were applied to the signal in Figure 5 in a rolling experiment, consisting of identifying and estimating the models starting on observation 384 385 and moving the data-set one sample ahead at a time. The results show that the ARIMA models were correct in essence, since the forecasts never produce any false alarm, in spite of the ups and downs of the signal, which might indicate the initial stage of development of a fault in the mechanism. 390

5. Conclusions

A condition monitoring has been developed for a level crossing (the type BR843). It is a critical element in the railway system. Electric motor voltage and current, hydraulic pressure and rotary position signals have been measured. 395

The system developed in this paper for the condition monitoring detects faults by means of comparing what can be considered a ‘normal’ or ‘expected’ shape of a signal with respect to the actual shape observed as new data become available. 400

The expected shape is computed as a forecast of a statistical model based only on fault-free movements of the level crossing observed in the past. These forecasts are compared online to the new incoming actual data and if the errors between the two are above an a priori defined critical level, 405 the system issues a fault warning.

Put in this way, the models forecast the time span a movement would take in case of absence of faults. If the expected time calculated by the model differs significantly from the observed time along a given movement, a fault is developing. 410

One modelling methodology implemented here to forecast the signal is the well-known ARIMA or Box–Jenkins methodology. Time-varying properties of the signal along the normal working operation of the level crossing are 415 tracked by automatic identification procedures. TRAMO is a freeware software package that has been employed for automatic identification and estimation of ARIMA models in the present application.

The Ljung–Box test and the Bera–Jarque have been 420 used for testing the resulting models concluding that they may be considered essentially correct.

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Dr Clive Roberts is a senior lecturer in Railway Systems and director of research for the Birmingham Centre for Railway Research and Education at the University of Birmingham. He is a whole system performance manager for Railway Research UK, the UK's Centre of Excellence in railway research. His first degree was in electronic engineering, while his Ph.D. focused on condition monitoring of the railway infrastructure. Over the past 13 years he has developed a portfolio of research in the fields of system modelling and simulation; fault detection and diagnosis; and data collection and decision support applied to railway traction, signalling, mechanical interactions and capacity. He currently leads a team of 11 research fellows and 10 Ph.D. students.

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