Prognostics with Autoregressive Moving Average for Railway Turnouts

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ABSTRACT

Turnout systems are one of the most critical systems on railway infrastructure. Diagnostics and prognostics on turnout system have ability to increase the reliability & availability and reduce the downtime of the railway infrastructure. Even though diagnostics on railway turnout systems have been reported in the literature, reported studies on prognostics in railway turnout system is very sparse. This paper presents autoregressive moving average model based prognostics on railway turnouts. The model is applied to data collected from real turnout systems. The failure progression is obtained manually using the exponential degradation model. Remaining Useful Life of ten turnout systems have been reported and results are very promising*.

1 INTRODUCTION

Railway turnout systems determine the direction of a train by moving rails and are considered to be one of the most important components of the railway infrastructure. Thus, reliability of turnout systems is critical for an effective railway management with increased availability & safety and reduced cost. For example, 14 million minutes of train delay has occurred in 2002-2003 causing approximately 560 million GBP in Britain (Marquez *et. al.*, 2008). Early identification and prediction of failures of turnout systems are important to increase the effectiveness of the railways. This paper presents a prognostic model using autoregressive moving average method for turnout systems.

Condition based maintenance (CBM) aims to identify and predict failures using sensory information collected from installed sensors. Failure identification (i.e. diagnostics) is basically a classification problem and relatively mature compared to failure prediction, which is basically a forecasting problem. There exist several diagnostics methods presented for railway turnout systems in the literature (Marquez *et. al.*, 2003), (Marquez *et. al.*, 2007a), (Roberts *et. al.*, 2002), (Marquez *et. al.*, 2007b), (Atamuradov *et. al.*, 2009), (Marquez *et. al.*, 2010). However, prognostics literature is relatively sparse.

Prognostic methods can be analyzed in three groups: evolutionary, state-based, and degradation prediction prognostics (Camci and Chinnam, 2010a), (Camci and Chinnam, 2010b). Failure progression is observed directly with the trend in features in evolutionary prognostics. States in failure progression are detected and forecasted in state based prognostics. Degradation is predicted in the last group using time series analysis. This paper uses one of the time series analysis methods, autoregressive moving average (ARMA), for degradation prediction.

The outline of the paper is as follows: section II describes turnout systems, section III presents times series model, ARMA, section IV presents the experimental setup and results, and section V gives the conclusion.

2 RAILWAY TURNOUT SYSTEM

Railway turnout systems determine the direction of a train by moving rails as seen in Fig 1. There are different types of turnout systems like pneumatic, hydraulic, and electro-mechanical based on the working principle. This paper uses an electro-mechanical system that consists of a motor, reduction gear, several bearings, drive-detection rods, switches etc. for experiment.

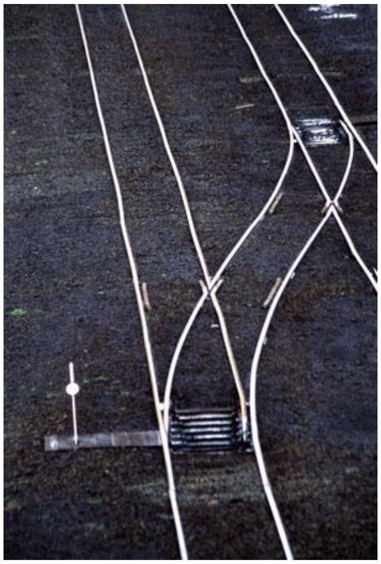

Fig 1: A Railway turnout system

3 AUTOREGRESSIVE MOVING AVERAGE MODEL BASED PROGNOSTICS

Autoregressive moving average (ARMA) models are used in time series analysis to describe time series data. Once the ARMA model is determined, it is used to estimate and predict future values of time series with the past values. ARMA model consists of two parts: an autoregressive (AR) part and a moving average (MA) part. The model is usually then referred to as the ARMA (p, q) model, where p is the order of the autoregressive part and q is the order of the moving average part.

The notation ARMA(p, q) refers to the model with p autoregressive terms and q moving average terms and is formulated as follows:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (1)$$

The summation expression with p number of terms with white noise (ε_t) comes from AR(p) model. The summation expression with q number terms and a constant (c) comes from MA(q) model. In training, the best p and q should be identified. Then, other parameters should be learned by fitting the model to the training data. Least squares regression is used in training to find the best values of the parameters that minimize the error term.

In this study, ARMA model is used to predict the future states of turnout system with exponential failure degradation. Failure degradation patterns obtained from training dataset are used in construction of ARMA model. Data collected from force sensor installed on railway turnout system are used in identification of the current health state. Then, next health state is forecasted using the ARMA with one-step prediction. Then, the predicted state is assumed to be the current state and the consequent state is forecasted. This process is repeated until the final health state is reached. Remaining useful life (RUL) is defined as the number of predictions made from current health state to the final state.

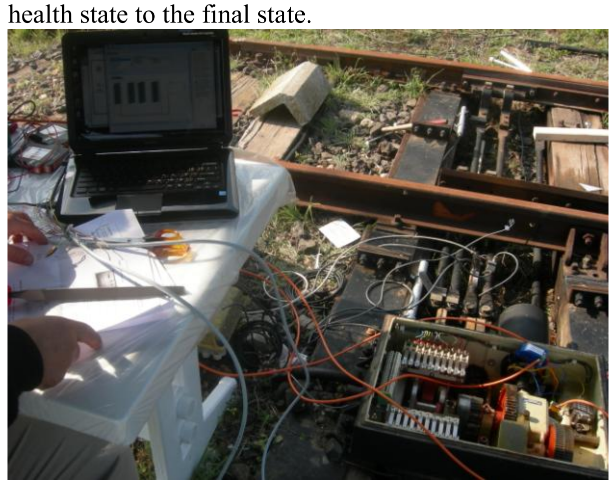

Fig 2: Railway turnout system with sensors installed

4 EXPERIMENT & RESULTS

The system under observation is an electro-mechanical system as shown in Fig. 2. Nine sensors were installed in the turnout system: two force sensors for each drive rod, one current, two voltage (separate sensors for forward and backward movement), two proximity sensors for each rail and two linear rulers for each drive rod. Force sensors are electrical sensing devices that are used to measure tension and compression forces. Tension cells are used for measuring a straight-line force "pulling apart" along a single axis; the force is typically denoted as positive. Compression tension cells are used for measurement of a straight-line force "pushing together" along a single axis; the force is typically annotated as negative. Current sensors measure DC current levels. They receive current inputs and provide outputs as analog voltage signals, analog current levels, switches, or audible signals. Voltage sensors are used to measure voltage in electric circuits. Proximity sensors measure the distance between the stock rail and switch rail of railway turnout systems. A linear position measuring sensor is installed on stretchers of the turnout system and measures the linear position of the switch rails. Time series data are acquired from both normal to reverse and reverse to normal movements of a turnout system. Labview is used for data acquisition.

The collected time series data is used for identification of the health of the system. When failures occur, the movement becomes more difficult leading to increased friction, force applied for pushing and pulling the rails, etc. There exist many different failure modes in a turnout system. Since it is difficult to analyze all, we have selected the contaminated slide chair failure mode, which is the most commonly seen one (Marquez *et. al.*, 2007a). Slide chairs are the metal platforms installed on twelve wooden traverses, on which the rail is located.
The discrete states in failure progression are obtained unnaturally. The state, in which metal platforms on all 12 traverses are oily, is the failure-free state. When only metal platforms on the three far-most traverses are dry, initial failure state occurs. Drying next traverse leads to next failure state. Hence, ten dryness states in slide chair of turnout system are obtained. Data for each state are collected after having the life and the time spent in each state for a sample. Data from an electro-mechanical railway turnout system is collected using several sensors as displayed in Fig. 3. Fig 4 and 5 displays the example of current and force data collected.

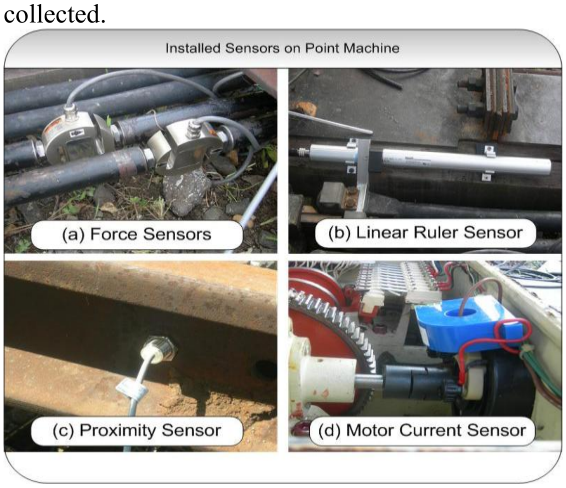

Fig. 3: Sensors installed in turnout systems

Electro-mechanical failures mostly follow a degradation path (Gabraeel *et. al.*, 2009). The duration of the degradation from maintenance/installation to the failure is long. Thus, it is difficult to obtain statistically enough samples to observe the real degradation. In this study, failure progression is created unnaturally with the strategy presented in (Eker *et. al.* 2010). It is necessary to model the real failure progression, since discrete states are obtained unnaturally.

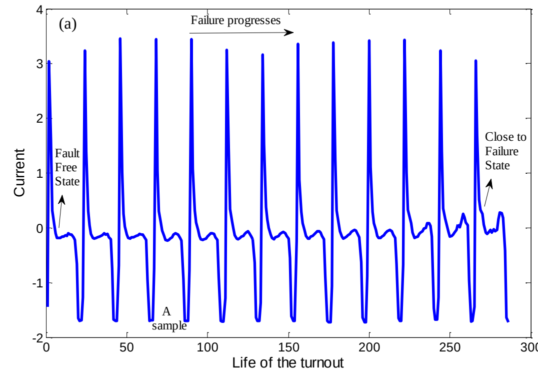

Fig 4: Current signals with failure progression from fault free to close to failure states

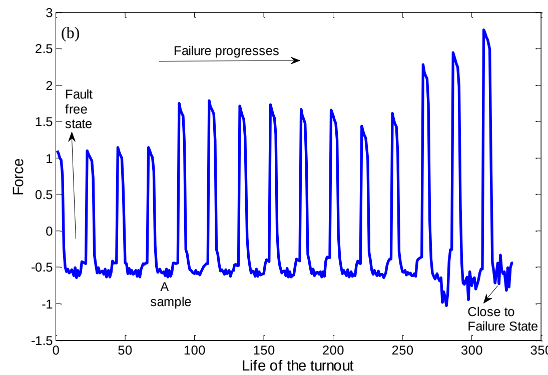

Fig 5: Force signals with failure progression from fault free to close to failure states

The exponential degradation model as in (2) is used. The degradations for different samples are obtained using this formula as shown in Fig. 3 with $\phi = 1$, $\mu_\beta = 0.8, \sigma_\beta = 0.1$. A threshold (22 in this case) is selected as the time of failure. Each degradation sample leads to a different failure time. Several failure progression levels are determined as shown with dashed horizontal lines in the figure. The failure progression state is obtained manually and number of samples corresponding to the time spent in to the length of the x-axis (time) of the degradation path (signal) when the y-axis falls in that state. Number of samples collected from a given health state is selected representing the time spent in that state. For example, more than five observations in fault-free state are seen in slowest failure progression sample in the figure, whereas third observation is seen to be in state 2 in the fastest failure progression sample.

$$S(t_i) = \phi e^{\left(\beta t_i + \varepsilon(t_i) - \frac{\sigma^2}{2}\right)} \tag{2}$$

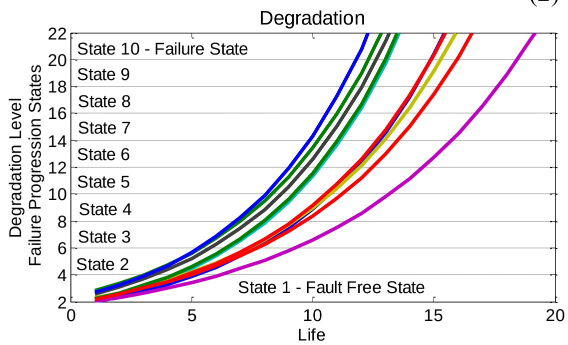

Fig 6: Failure degradation and discrete health states

When a time series data collected from sensors is given, the state of the turnout system has been identified. K-means clustering algorithm is used for identification of the health state. Then, ARMA model is used to predict the future states of the system in degradation path. Fig. 7 illustrates the failure progression forecasting.

In presented system, ARMA(1,1) model is used which gives reasonable fit and prediction results with trial-error method. Increasing p and q values increases the number of parameters to be estimated, which increases computational time and required training data size.

Prediction of lifetime using ARMA can be expressed in two parts: construction of the model and prediction of state steps. One sample is left for testing and the rest is used for training. This is repeated with one-leave-out cross validation method. After the ARMA model is built, a sample is selected to be estimated.

Reaming Useful Life (RUL) is defined as the number of predictions from current state until the failure states is reached. Fig 8 displays the real and predicted RUL for ten turnout systems. Data from first state to the failure state is ordered as displayed in Fig. 5 and Fig. 6. Data from initial state to the failure state is selected in order. Health state of the selected data is identified. Then RUL is calculated for the selected data. This is repeated for all the data from initial state to the failure state of all samples. Fig 8 displays the real and predicted RUL values for all samples. x-axis in the figures represent the current age of the system, whereas the y-axis represent the remaining useful life of the system. The solid linear line is the real RUL. Dashed line is the predicted remaining useful life of the system. The similarity of these two lines gives the effectiveness of the prediction method. The higher the similarity, the better the prediction method is.

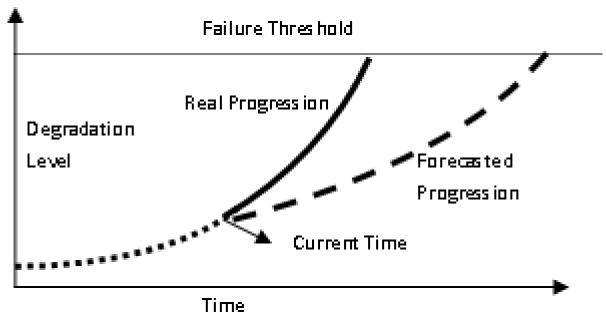

Fig 7: Failure Progression Forecasting

RMSE and r-square are used as similarity measure between real and predicted remaining useful life for evaluation of RUL prediction in the literature. Fig 9 shows the r-square values of real and estimated RUL of each turnout. The average of r-square values is 0.9758. The higher the similarity, the higher the r-square value is. RMSE values are an error rates of estimated RUL compared to real RUL. The higher the similarity, the lower the RMSE value is. Fig 10 displays the RMSE values of the ten turnout systems. The average of RMSE values is 0.65.

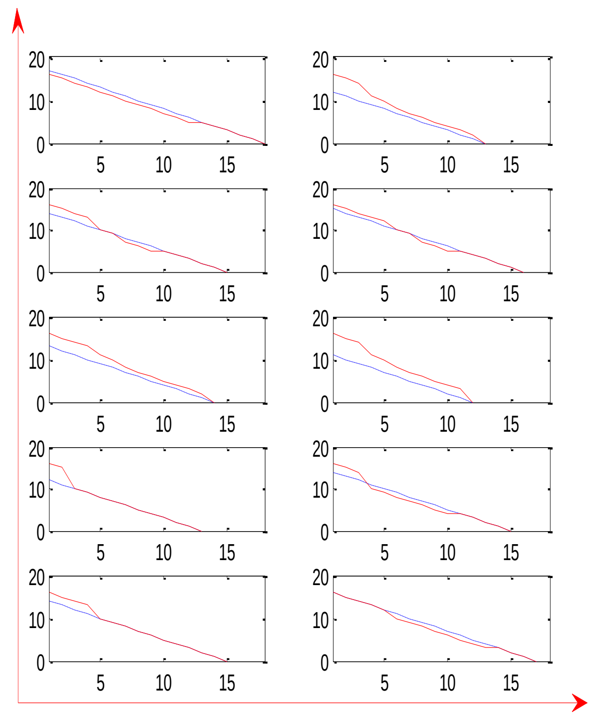

Fig 8: Estimated (dashed) and Real (solid) RULs for ten turnout system

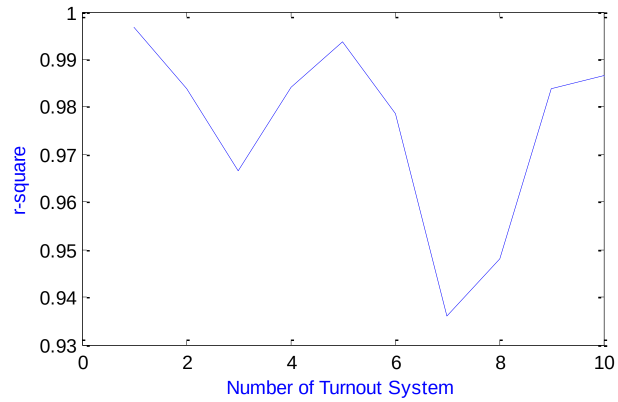

Fig 9: r-square values of estimated and real RUL for ten turnout systems

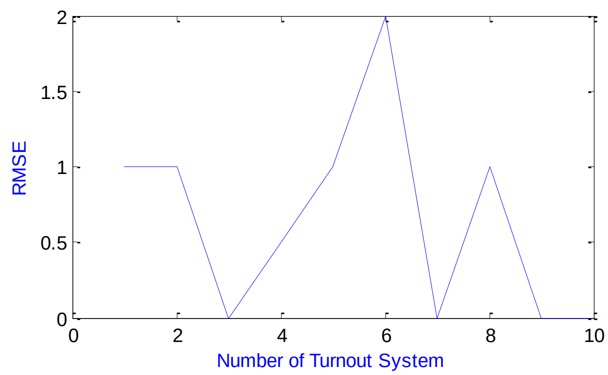

Fig 10: RMSE values of estimated and real RUL for ten turnout systems

5 CONCLUSION

Even though studies exist on diagnostics on railway turnout system in the literature, prognostics studies reported in the literature is limited. In this paper autoregressive moving average model (ARMA) is used for prognostics on railway turnout systems. The model is applied to data collected from real turnout systems. The results are very promising and reported in the paper.

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NOMENCLATURE

ϕ Constant in exponential degradation model

β Random variable following s-normal distribution

μ_β Mean of β

σ_β^2 Variance of β

p Order of the autoregressive part

q Order of the moving average part.

ε_t White noise

φ_i Autoregressive parameter

θ_i Moving average parameter

c A constant

X_t Value of time series at time t

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Ian K Jennions is the director of the Integrated Vehicle Health Management (IVHM) Centre at Cranfield University, UK. His PhD work at Imperial College, London, led to a significant improvement in modelling of missile exhausts for the UK Ministry of Defence. He has over 30 years of industrial experience mostly for a variety of gas turbine companies such as Rolls-Royce, General Electric Aircraft Engines. In 1985 he moved to and led the take-up of CFD for the aerodynamic design of turbomachinery. He formed a strong group working on all elements of the turbomachinery design system with the methods developed being used in a number of engine projects. The move to ABB in 1994 broadened his role, becoming involved in heat transfer, air systems and proof of concept projects as well as CFD. He returned to Rolls-Royce in 1998 to be in charge of combustion and turbomachinery in their Energy Business, and was involved with some innovative methods of controlling combustion instabilities. A couple of roles in the R&T organisation led him to be EHM Global Capability Owner, a corporate role spanning all of Rolls-Royce’s businesses and main engineering sites.