A Real-Time Condition Monitoring System by using Seasonal ARIMA Model and Control Charting

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Abstract: *This paper is concerned with research on early-failure monitoring systems for safety of railway systems. The work presented here have led to the development of ideas and techniques for the employment of time series modelling and control charting for on-line temperature monitoring of railcar brakes. A software package implementing the real-time monitoring scheme is presented. The temperature signal is sampled and the readings are filtered using a time-series model. In particular, a seasonal ARIMA model is exploited. The filtered signal, which has well defined statistical properties, is then plotted against proper control limits. The motivation of the research is the need for improved reliability of equipment and quality of service to metro passengers.*

Keywords: Seasonal ARIMA model, SPC, FVC, SCC.

1. Introduction

A fault is defined as an undesired state that may lead to a malfunction or failure of a system. Generally, a fault is identified by signalling an unpermitted departure of one or more characteristic property of a variable from an acceptable behaviour.
For the enhancement of safety and reliability, advanced methods of supervision become increasingly important for many technical processes and systems. Supervisory methods serve to signal undesired or not permitted process states, and eventually to take appropriate actions in order to maintain the operation and to avoid damage or accidents. Supervision methods are especially important in the case of safety related to transportation systems like aircraft, trains, automobiles, as well as for production processes as power plants and chemical plants.
A general survey of supervisory methods is given by Isermann (2005). In the case of a dangerous process state, three main supervisory methods can be distinguished: 1) Monitoring (measurable variables are checked and alarms are generated for the operator). 2) Automatic protection (an appropriate counteraction is automatically initiated). 3) Fault diagnosis (based on measured variables, a fault diagnosis is performed and decisions for counteractions are generated for the operator).
Regardless of the specific purpose of the supervisory method, the detection of faults in the processes is obtained by modelling the dependencies between different measurable signals. These dependencies are expressed by mathematical and statistical models. As a matter of fact, measured signals of real process typically show oscillations that are of stochastic nature. If changes in these signals can be related to faults in the process, a supervisory method can be developed by using Statistical Process Control (SPC) techniques.
This paper presents the application of a SPC method that uses time-series filters and control charting for on-line condition monitoring of railway equipment. In particular, a statistical monitoring system of car brakes temperature, which can provide advanced warning to train operator of an overheated bearing condition, is discussed. The motivation for this research is the need for

improved reliability of equipment and quality of service to metro passengers. The temperature signal is sampled one time in about two minutes and the readings are filtered using a time-series model. The filtered signal, which has well defined statistical properties, is then plotted against proper control limits.

2. Literature review

One of the major techniques of SPC is the control chart. In its basics form, a control chart compares process observations (or a function of such observations) to a pair of control limits. A fundamental assumption for the development of a control chart is that process observations are independently distributed. However, readings sampled over time from a physical variable (such as brakes temperature) exhibit, in general, autocorrelation. In such cases, control methods, which allow for violations of the independence assumption, must be used. Several approaches were presented in the literature. Three general charting techniques can be identified to handle autocorrelation.

- The first technique is to use time series models to fit the data, and then apply standard control charts.
- The second technique consists in apply control charts with adjusted control limits, which account for the correlation structure of the data.
- The third technique consists in monitoring specialized statistics of the original observations.

The first technique was proposed by Alwan and Roberts (1988), which presented the use of time series modelling to detect special causes of variation by using the special-cause control (SCC) chart. The SCC chart is the traditional Shewhart's chart of the residuals. The basic idea of the SCC chart is that if the natural cause of the process variation can be modelled by a time series model, then the residuals of the fitted model will explain the special cause to the process, if any.

In the second category of charting techniques for autocorrelated processes, Wardell *et al.* (1994) suggested that *k*-sigma limits on a standard Shewhart's control chart could be used, with proper values of *k*. Zhang (1997) used simulation to find out the best choice of *k* for certain time series models so as to make the in-control performance as close as possible to that of a standard Shewhart's chart. For small autocorrelation, the properties of this chart do not differ greatly from the properties of a Shewhart's chart applied to independent data.

In the third category of charting techniques for autocorrelated processes, the Exponential Weighed Moving Average (EWMA) statistic applied on the original autocorrelated observations have been frequently recommended. More recently, Zhang (1998) developed a chart for using a EWMA statistic to monitor a stationary (ST) process: the EWMAST chart. Such a chart is superior to the SCC and Shewhart charts when the process autocorrelation is not very strong and the mean change is not large.

From a performance perspective, Wardell *et al.* (1994) applied the three techniques, i.e. SCC, EWMA and Shewhart's control charts, for monitoring autocorrelated processes in a special case of time series model (the first order autoregressive first order moving average – ARMA(1,1) – model). By comparing the performance of the SCC chart, in signalling out-of-control behaviours of the monitored process, to that of the Shewhart chart and EWMA chart, they concluded there is no a unique best chart to use for every type of autocorrelated process.

2. The method implemented

In this paper, a time series model is exploited to fit data. The technique consists of filtering out autocorrelation by an autoregressive integrated moving average (ARIMA) model, following the techniques of Box *et al.* (1994). Then, if the time series model is accurate enough, the residuals (i.e., the prediction errors) are statistically uncorrelated to each other, and a standard Shewhart's control chart (the so-called SCC chart) can be applied to them (Alwan and Roberts 1988).

The ARIMA model of parameters (p,d,q) is described in following equation (1).

$$\begin{aligned}&\phi(B)w_t = \theta(B)\varepsilon_t,\\&\phi(B) \equiv 1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p\\&\theta(B) \equiv 1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q\\&w_t \equiv \nabla^d z_t \qquad (d \geq 0)\end{aligned} \tag{1}$$

where the difference operator ∇ is defined as follows.

$$\nabla z_t \equiv z_t - z_{t-1} \quad \nabla^2 z_t \equiv \nabla(\nabla z_t)\cdots \tag{2}$$

and the backward shift operator B is defined by (3).

$$Bz_t \equiv z_{t-1} \qquad B^2 z_t \equiv B(Bz_t) = z_{t-2} \quad \cdots \tag{3}$$

z_t is the original reading collected at time t, w_t is the respective differentiated signal, and ε_t is the residual.
In the reference test case, it has been observed that brakes temperature data show seasonal periodic patterns. These patterns can be modelled by creating ARIMA models for the seasonal variation as well as for the individual samples.
The composite model is known as a Seasonal ARIMA model of parameters $(p,d,q)\times(P,D,Q)_s$, where p is the number of significant autocorrelations, d is the number of differentiations, q is the number of significant moving average terms within each season, and P, D, Q are the autocorrelations, differentiations and moving average terms, taken across seasons of duration s.
The complete Seasonal ARIMA $(p,d,q)\times(P,D,Q)_s$ model is expressed by equation (4):

$$\begin{aligned}&\phi(B)\Phi(B^s)w_t = \theta(B)\Theta(B^s)\varepsilon_t,\\&w_t \equiv \nabla_s^D(\nabla^d z_t)\end{aligned} \tag{4}$$

A model can be obtained from the collected data when the process is in control. Once a model has been developed, it can be used to forecast (or predict) each new value. The difference between the forecast value and the actual value is the forecasting error, or residual.
In summary, the real-time SPC scheme takes temperature sensor data that are auto-correlated and then feeds them into an appropriate time-series filter Seasonal ARIMA $(p,d,q)\times(P,D,Q)_s$ produce independent and identically distributed residuals. A control chart is then applied on the residual sequence.

3. Application to real-time process data

The monitoring system takes as input the data of railroad brakes temperature. In this work, process data were simulated. Then, it feeds process data into an appropriate time-series filter.
The Seasonal ARIMA $(p,d,q)\times(P,D,Q)_s = (2,2,0)\times(3,2,4)_{16}$ was selected for this application. Indeed, this model produced independent, identically and normally distributed residuals for temperature data of railroad brakes: $\varepsilon_t \sim NID(0,\sigma^2)$.

The statistical software MINITAB® was exploited in order to: 1) estimate model parameters, 2) check the adequacy of the model and 3) estimate the variance of the residuals. Eventually, a SCC chart was designed on the residuals.

A software package was then developed to implement the real-time monitoring scheme. It includes four modules: 1) data manipulation, 2) Seasonal ARIMA filtering, 3) control charting and graphical display, and 4) alarm generation. These operations were implemented in MATLAB®.

Following Figure 1 illustrates the graphical output of the software package implemented in MATLAB®. From left to right, each panel of Figure 1 represents respectively: 1) the time series plot of actual temperature data, 2) Fitted Value Chart (FVC), i.e., a graph of the actual time series along with the fitted values, 3) SCC chart, i.e., the Shewhart's control chart of residual errors between actual data and predicted values. The SCC consists also of a central line and of upper and lower control limits.

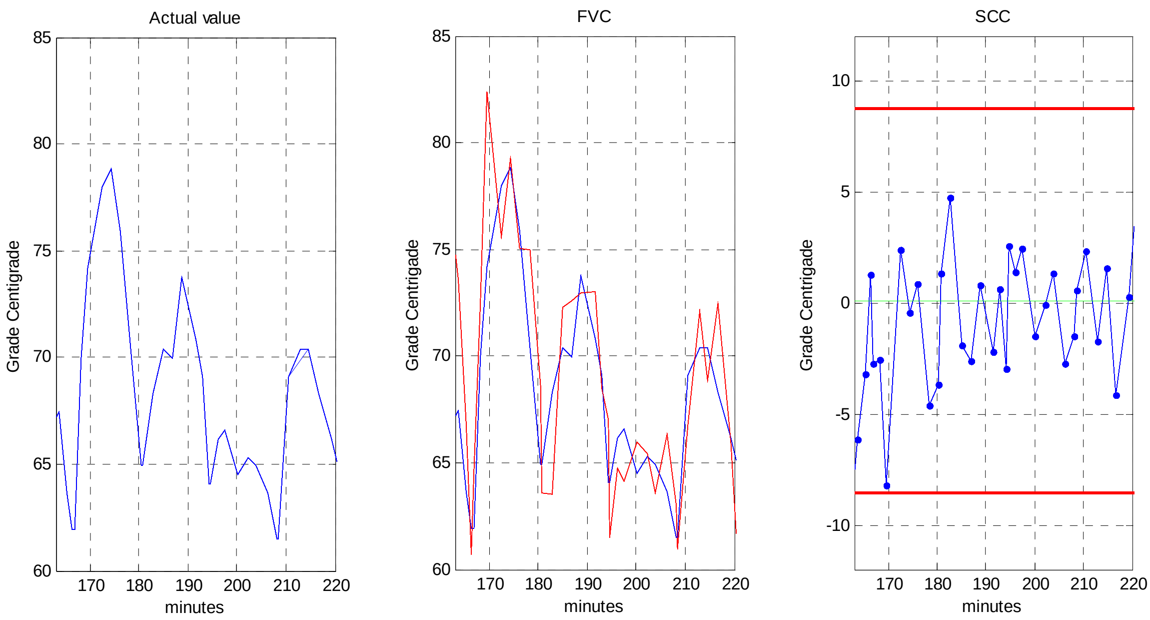

Figure 1: Output plots produced by MATLAB®. From left to right panels: the actual temperatures, the FVC, the SCC chart with central line and control limits (upper and lower)

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