A dynamic probabilistic modeling of railway switches operating states

Faicel Chamroukhi[1], Allou Samé[1], Patrice Aknin[1], Marc Antoni[2]

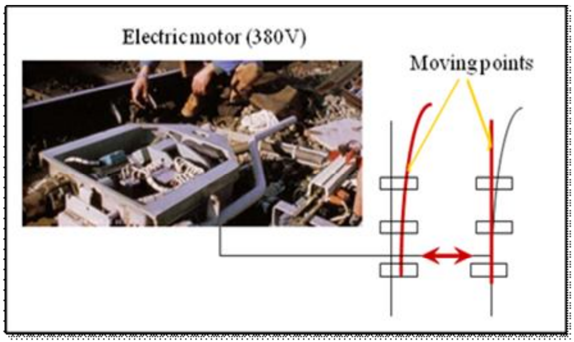
[1]IFSTTAR, 2 rue de la Butte Verte, 93166 Noisy-le-Grand Cedex, France
{chamroukhi,same,aknin}@ifsttar.fr

[2]SNCF, Direction de l'Infrastructure, 17 rue d'Amsterdam, 75379 Paris Cedex 08, France
marc.antoni@sncf.fr

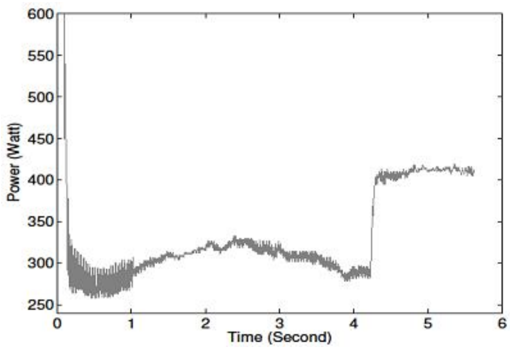
Abstract: The remote monitoring of the railway infrastructure and particularly the switch mechanism is of great interest for railway operators. The problem consists in detecting earlier the presence of defects in order to alert the concerned maintenance service before a breakdown occurs. For this purpose, this paper introduces a new probabilistic-based approach to dynamically modeling the evolution of condition measurements acquired during switch operations. It consists of two steps. The feature extraction from the electrical power consumption signals which aims at summarizing each signal by a low dimensional feature vector. Then, a specific autoregressive model is proposed to model the dynamical behavior of the switch mechanism.

1. Introduction

The remote monitoring of the railway infrastructure and particularly the switch mechanism continues to be of great interest for railway operators because its operating state directly impacts the availability of the overall railway network. The problem consists in detecting earlier the presence of defects (electrical, mechanical or civil engineering defects) in order to alert the concerned maintenance service before a breakdown occurs. Due to its evolving operating conditions over time, the diagnosis of the switch mechanism has to be performed by exploiting successive measurements (or sequences) acquired during the working process. In this case, each measurement represents the electrical power consumed during a switch operation, as shown in figure 1b. The particular switches considered in this paper are driven by an electric motor and equipped with a clamp locking system so-called VCC (see figure 1a).



(a)



(b)

Figure 1. The switch mechanism (a) and a signal showing the electrical power consumed during a switch operation without defect (b).

Several approaches based on probabilistic modeling have been proposed to continuously monitor complex systems, including the more general approach based on Hidden Markov Model (HMM) [8]. Especially regarding the switch mechanism, Diego et al. [ref] considers a dynamical correlation analysis including a state-space representation to earlier detect failures.

In this paper, a novel probabilistic-based approach is proposed to dynamically modeling the switch operating state over time. This approach is based on the following two steps. First, we summarize each curve (corresponding to a switch operation) by a low dimensional feature vector by using a specific regression model [7] whose parameters are taken to be a feature vector. In other words, this step consists in converting a sequence of curves acquired during successive switch operations into a sequence of relevant multidimensional feature vectors. Then, based on the formed sequence of multidimensional data, the degradation level of the point mechanism is dynamically assessed by switching between various autoregressive models, the switching mechanism being controlled by a stochastic process. The resulting model is called the switching autoregressive model with a hidden logistic process abbreviated as ARHLP [2].

This paper is organized as follows: section 4 briefly recalls the feature extraction methodology from the signals of power consumption. Then, section 3 presents the probabilistic dynamical model and its parameters estimation technique, and shows how it can be used to predict the state of a switch operation. The proposed approach is evaluated in section 4 using data acquired from switch operations on the French railway network.

2. The feature extraction from the electrical power signals

The goal of this step is to summarize each signal by a low dimensional feature vector. A specific regression model [3], whose parameters are used as feature vector, is adopted. The strength of this model is to automatically fit different polynomial sub-regression models to each signal. The model parameters are estimated by the maximum likelihood method performed by the so-called Expectation Maximization (EM) algorithm [4]. An illustration of the results obtained by applying this approach to real switch operations signals is shown on Figure 2.

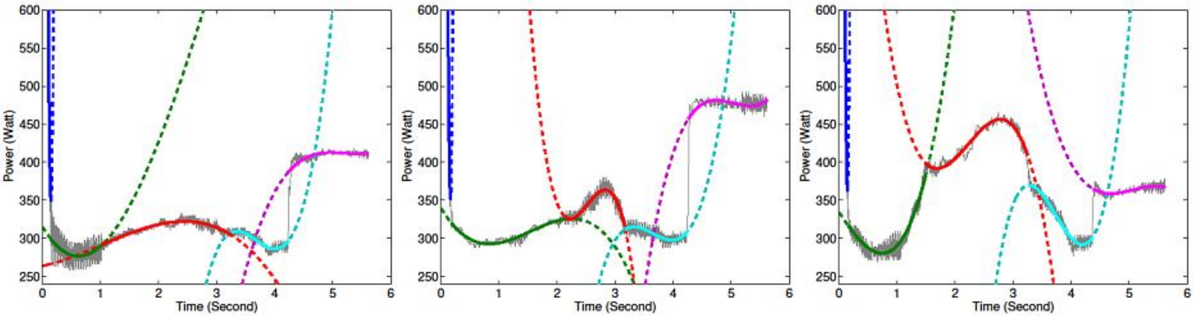


Figure 2. Three signals and their estimated regression models: (left) without defect, (middle) with minor lubrification defect and (right) with critical lubrification defect.

After modeling each signal, we obtain a parameter vector of dimension 33 for each signal. This parameter vector is then used as the feature vector describing the signal.

3. The dynamic modeling of condition measurements using a switching autoregressive model

The data used in this step are made with the parameters extracted from the previous step. At each instant time, the system (the switch mechanism) is assumed to be described by one specific autoregressive model supposed to be representative of its operating state and the switching from one autoregressive model to another one is controlled by a discrete hidden logistic process. The proposed model is described in the next section.

3.1. The switching autoregressive model governed by a hidden logistic process

The ARHLP (dynamical autoregressive model with a hidden logistic process model) is an extension of the model presented in [5], which consists of several local multivariate autoregressive models and a latent logistic process that allows for switching between these autoregressive models. In this context, each autoregressive model is related to an operating state. Another similar autoregressive model can be found in [8] where the switching from one state model to another one is controlled by a discrete Markov chain.

The observation sequence *$(y_1,...,y_T)$* is assumed to be generated by the following multivariate autoregressive model governed by the stochastic process *$(z_1,...,z_T)$*:

$$y_t = B_{z_t} y_{t-1} + e_t,\ \ e_t \sim \mathrm{N}(0, \Sigma_{z_t})\ \ (t = 2,...,T)\,. \tag{1}$$

The variable z_t is a latent discrete random variable which takes its values in the finite set *{1...K}*. It represents the class label of the state generating y_t, B_{z_t} is the *dxd* dimensional matrix of the autoregressive model coefficients associated with the state z_t, Σ_{z_t} is the *dxd* covariance matrix for the autoregressive model z_t, and the variables e_t are independent random variables in R^d distributed according to a standard multivariate Gaussian distribution representing an additive noise. Figure 3 gives a graphical representation for this model. As it can be seen on this representation, the variable y_t is influenced by the state z_t and the past observation y_{t-1}.

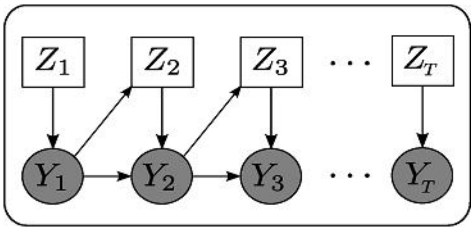


Figure 3. Graphical model structure for the proposed dynamical model (ARHLP).

In this specific autoregressive model, the stochastic process $(z_1,...,z_T)$ controls the switching from one autoregressive model to another among K models. Thus, unlike the basic autoregressive model [5], which assumes constant autoregressive model parameters B and ∑ over time, the proposed model is based on time-varying parameters. It is thus able to capture the non-stationary behavior of the switch mechanism degradation process. We assume that the underlying hidden switching process $\mathbf{z} = (z_1,..., z_T)$ is logistic, that is the hidden variable z_t is distributed according to a multinomial distribution $M(1,\pi_1(y_{t-1};\mathbf{w}),..., \pi_K(y_{t-1};\mathbf{w}))$ where the conditional probability of each state k $(k=1,...,K)$ is given by:

$$\pi_k(y_{t-1};\mathbf{w}) = p(z_t = k \mid y_{t-1};\mathbf{w}) = \frac{\exp(\mathbf{w}_k^T y_{t-1})}{\sum_{k'=1}^{K}\exp(\mathbf{w}_{k'}^T y_{t-1})}, \quad (2)$$

where the d-dimensional parameter $\mathbf{w}_k$ is associated with the kth logistic component and $\mathbf{w} = (\mathbf{w}_1,..., \mathbf{w}_K)$.

The proposed model is then parameterized by the parameter vector $\Psi = (\mathbf{w}, B_1,..., B_K, \Sigma_1,..., \Sigma_K)$. The parameter estimation is performed by iteratively maximizing the likelihood function using a dedicated EM algorithm [4][6]. This EM algorithm is given in details in [2].

Let us notice that, the proposed modeling approach assumes that the sequence of signals covers all the states of the switch mechanism. Basing on this assumption, the next two paragraphs thus show how the ARHLP model can be used for state identification and prediction.

3.2. State identification

Suppose we have estimated the parameters of the different states from a training sequence observed up to time T. The state of a new observation y_t (in this case y_t is the feature vector extracted from the signal acquired at the time step t) can be identified by assigning y_t to the state $\hat{z}_t$ using the so-called Maximum A Posteriori (MAP) rule:

$$\hat{z}_t = \arg\max_{1\le k\le K} p(z_t = k \mid y_1,..., y_t;\hat{\Psi}), \quad (6)$$

where

$$p(z_t = k \mid y_1,..., y_t;\hat{\Psi}) = \frac{\pi_k(y_{t-1};\hat{\mathbf{w}})N(y_t;\hat{B}_k^T y_{t-1},\hat{\Sigma}_k)}{\sum_{l=1}^{K}\pi_l(y_{t-1};\hat{\mathbf{w}})N(y_t;\hat{B}_l^T y_{t-1},\hat{\Sigma}_l)} \quad (7)$$

is the posterior probability of the state k for the new observation y_t given the previous observation y_{t-1} and the estimated models parameters $\hat{\Psi}$ **.**

3.3. State prediction

The proposed dynamical model can also be used to forecast switch operations state. The goal in this case is to predict the state z_{t+1} of a future observation y_{t+1} $(t \; ^3 \; T)$ not yet observed, given the history up to time t. This consists of maximizing with respect to k the prediction probability

$$p(z_{t+1} = k \mid y_1,\ldots,y_t;\hat{\Psi}) = p(z_{t+1} = k \mid y_t;\hat{\Psi}) = \pi_k(y_t;\hat{\mathbf{w}}) \quad (8)$$

which is none other than the probability of the logistic process given in Equation (2).

4. Experimental study

This section is devoted to the evaluation of the proposed approach in terms of operating state prediction, using a database of real signals issued from the switch operations.

4.1. Experimental setup

We consider a sequence of *120* real switch operation signals classified into three states provided by an expert:

- *state k=1*: no defect state;
- *state k=2*: minor defect state;
- *state k=3*: critical defect state.

The cardinal numbers of those three states are n_1=35, n_2=40 and n_3=45 respectively. Figure 4 shows a sequence of signals acquired during successive switch operations.

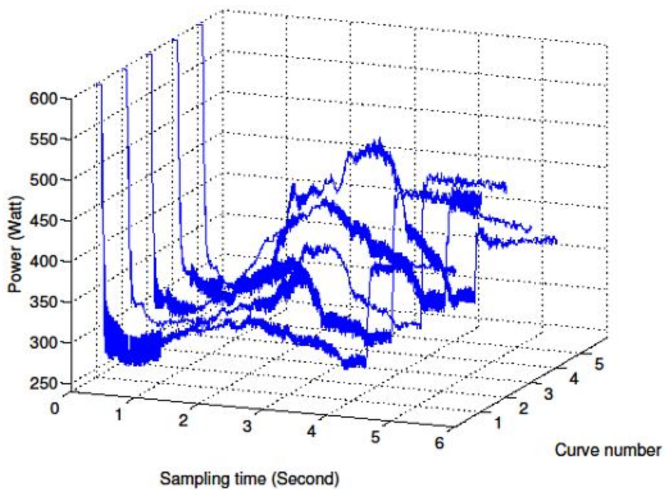


Figure 4. Examples of signals acquired during successive switch operations.

The true operating state sequence is shown in Figure 5.

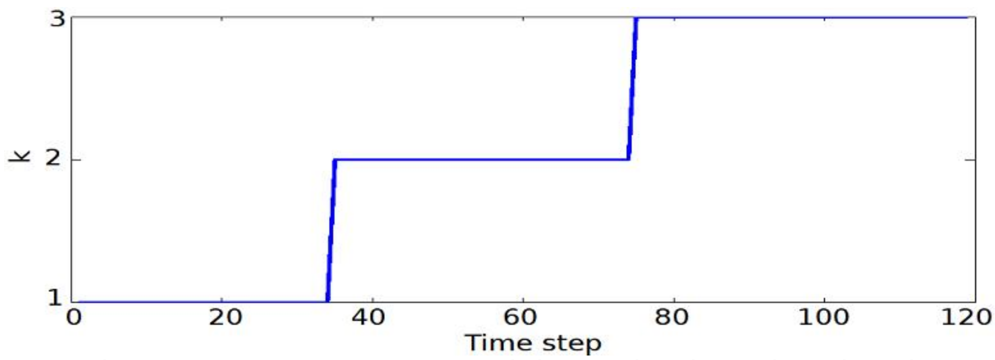


Figure 5. True state sequence of switch operation signals (120 signals).

4.2. Obtained results

In this section we report the modeling results obtained by the proposed ARHLP approach for the dynamical modeling of the switch operating states. Figure 6 shows the prediction probabilities computed according to Equation (8). The state prediction error rate in this case equals 10.92 %.

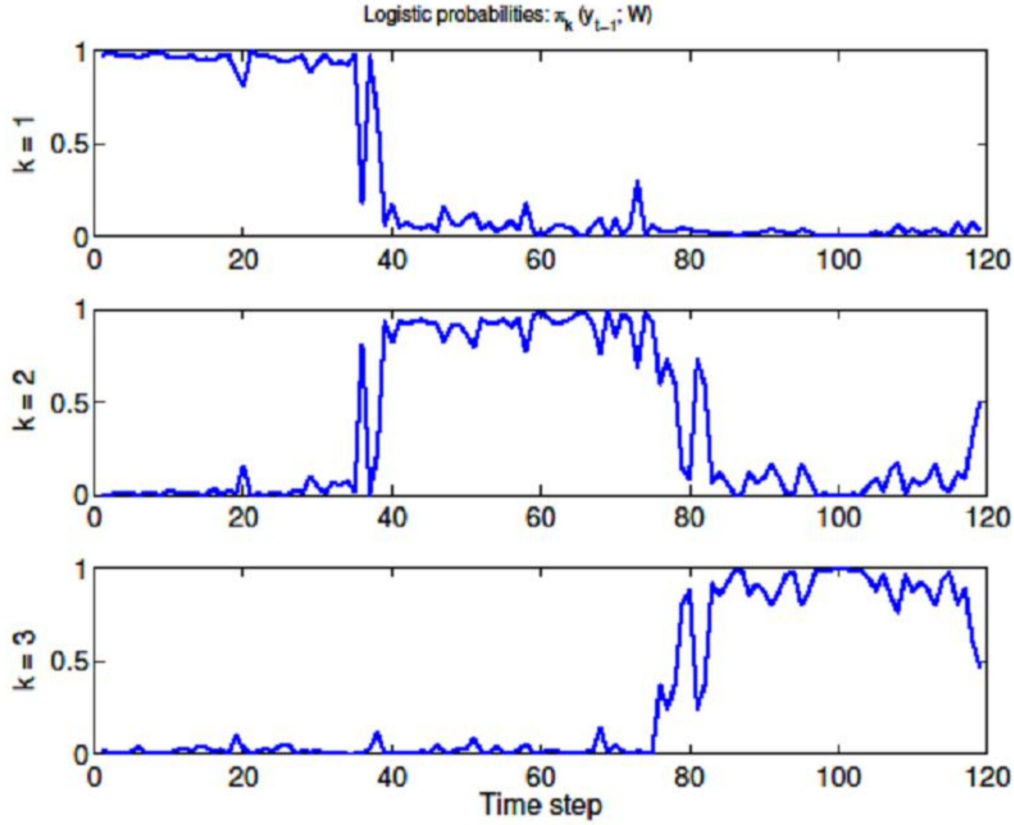


Figure 6. Prediction probabilities over time obtained with the ARHLP model from the signal sequence.

Figure 7 shows the results in terms of operating state identification, that is the sequence obtained by maximizing, at each time step, the posterior state probability computed according to Equation (6). The error percentage between the true sequence and the estimated MAP sequence equals 9.24.

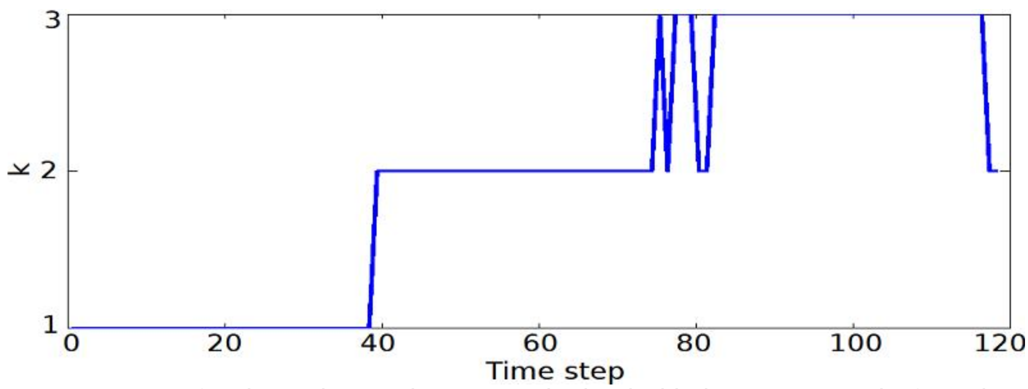


Figure 7. Sequence of estimated operating states obtained with the ARHLP model from the switch operation signals

5. Conclusion

This paper has introduced a probabilistic-based approach for monitoring the railway switches. The proposed model operates on relevant features preliminarily extracted from the power consumption curves acquired during successive switch operations. It consists in switching between various local autoregressive models that can be associated with the different operating states of the system, the switching between different models being controlled by a discrete hidden stochastic process. The model parameters identification is performed by the Expectation Maximization (EM) algorithm which is particularly adapted to this specific context, using a sequence of power consumption signals covering various operating states. Once the model parameters have been identified using the training sequence, the operating states of new operations are identified and predictions are made for future operations. The experimental study conducted on real switch operation signals has shown encouraging results in terms of operating state identification and prediction. Even if the proposed approach can be used for the on-line prediction of operating states, it requires the probabilistic model parameters to be learnt off-line using a data sequence covering all the operating states. The main prospect of this research will then be to develop a self adaptive approach in which the model parameters will be recursively adapted over time.

References

[1] G. Celeux, J.C. Nascimento, and J.S. Marques. Learning switching dynamic models for objects tracking. *Pattern Recognition,* 37(9):1841–1853, September 2004.

[2] F. Chamroukhi. Hidden *process regression for curve modeling, classification and tracking*. Thèse de doctorat, Université de Technologie de Compiègne, 2010.

[3] F. Chamroukhi, A. Samé, G. Govaert, and P. Aknin. Time series modeling by a regression approach based on a latent process. Neural Networks, 22(5-6):593–602, 2009.

[4] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, B,* 39(1):1–38, 1977.

[5] L. Harrison, W. D. Penny, and K. Friston. Multivariate autoregressive modeling of fMRI time series. *Neuroimage,* 19(4):1477–1491, August 2003.

[6] G. J. McLachlan and T. Krishnan. *The EM algorithm and extensions*. New York: Wiley, 1997.

[7] P. Smyth. Hidden markov models for fault detection in dynamic systems. *Pattern Recognition*, 27(1):149–164, 1994.

[8] C.S. Wong and W.K. Li. On a logistic mixture autoregressive model. *Biometrika,* 88(3):833–846, 2001.