Proceedings of the 2016 Winter Simulation Conference
T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, and S. E. Chick, eds.

MODELING AND ANALYZING THE BREAKDOWN PROCESS

Shu Pan

School of Mathematics
University of Southampton
SO17 1BJ
UNITED KINGDOM

Athanassios N. Avramidis

School of Mathematics
University of Southampton
SO17 1BJ
UNITED KINGDOM

ABSTRACT

An Operation Dependent Environment Change (ODEC) model has been proposed to model the breakdown process of a real production line. The model allows for an individual machine's breakdown rates to alternate between low and high when the machine is operational. The ODEC model is natural and allows for the times between breakdowns to be positively auto-correlated, which is what exhibits in the data from an engine production line of a major UK automotive manufacturer. A Markov-modulated Poisson Process with two hidden Markov states (MMPP2) method has been proposed to estimate the transition rates. This enables us to solve the performance measure of the production line, i.e. the throughput, analytically using a Markovian model.

1 INTRODUCTION

In this paper, we aim to fit a model for the breakdown process of a real production line, the data of which come from a major UK automotive manufacturer. Preliminary data analysis shows that the inter-breakdown times are not exponentially distributed, and there is statistically significant auto-correlation between the inter-breakdown times. To overcome the limitations of a single-rate Poisson model and the empirical distribution function model, we propose and estimate a Markov-modulated Poisson Process with two hidden Markov states (MMPP2) (Rydén 1996). The estimated generator of the hidden chain and the Poisson rates enable us to solve the performance measure, i.e. the throughput of the line, analytically using a Markovian model.

The model we proposed is an Operation Dependent Environment Change (ODEC) model, which allows for an individual machine's breakdown rate to alternate between low and high when the machine is operational. This model is natural and allows for the times between breakdowns to be positively auto-correlated, which is what the data often exhibits. The results show that the estimated MMPP2 model matches the empirical moments of order 1 and 2 well, and the potential lack of fit of MMPP2 could be addressed by fitting a large-size MMPP, e.g. with 3 states.

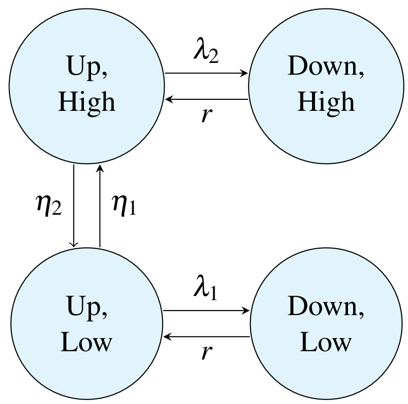
2 DEFINITIONS

- Time Dependent Global Environment Change (TDGEC) - There is a global variable which affects the breakdown rates of all the machines simultaneously, i.e. weather change or new operator in the line. Since all the events contain some information, the likelihood is very complex to calculate.
- Time Dependent Local Environment Change (TDLEC) - There is a local variable which allows for an individual machine's breakdown rate to alter at any time. Under this model, the likelihood is not the standard assumed in a Hidden Markov Chain. This is because the Hidden chain moves during down times, but failures are not possible during the down times.

- Operation Dependent Environment Change (ODEC) - There is a local variable which allows for an individual machine's breakdown rate to change only when the machine is operational. This is inherent to the machine operating, i.e. tool wear, and can be estimated using Maximum Likelihood Estimation.

3 ODEC MODEL DESCRIPTION

In the ODEC model, the environment can only change when the machine is operational (up). The transitions between states for each individual machine are illustrated in the figure below, where η_1 and η_2 are the generator of the hidden chain, meaning the machine breakdown rates switch from low to high and high to low, respectively. λ_1 and λ_2 are the high and low breakdown rates. r is the repair rate.



4 ESTIMATING AN MMPP2 MODEL

The table below summarizes the results from fitting an MMPP2 model for four representative machines. We show the estimates of model parameters: generator of the hidden chain (η_1, η_2), and the Poisson rates (λ_1, λ_2). In the remaining columns, we show how well the estimated mmpp2 model matches the empirical moments of order 1, 2, and 3. The parameters are solved by using the R package "HiddenMarkov" (Harte 2015).

Observations	Max acf	Lag	η_1	η_2	λ_1	λ_2	$\hat{\mu_1}/\mu_1$	$\hat{\mu_2}/\mu_2$	$\hat{\mu_3}/\mu_3$
1623	0.26	1	0.05	11.23	0.12	22.60	0.95	0.93	0.69
1795	0.21	2	0.10	17.31	0.15	21.53	1.07	0.97	0.70
1510	0.16	1	0.08	13.37	0.12	17.67	1.06	0.98	0.70
1804	0.22	1	0.07	5.20	0.16	9.07	1.02	0.92	0.72

5 CONCLUSION

MMPP2 provides sensible estimates of the transition rates of auto-correlated data. The potential lack of fit of MMPP2 could be addressed by fitting a large-size MMPP, e.g. with 3 states. This enables us to solve the performance measure of the production line analytically using a Markovian model. In the ongoing and future work, our models will feed detailed simulation models of the line, and hopefully provide a more realistic model.

REFERENCES

Harte, D. 2015. *HiddenMarkov: Hidden Markov Models*. Wellington: Statistics Research Associates. R package version 1.8-4.

Rydén, T. 1996. "An EM algorithm for estimation in Markov-modulated Poisson processes". *Computational Statistics & Data Analysis* 21 (4): 431–447.