



Faculty of Information and Communication Technology

A DATA-DRIVEN PROGNOSTIC MODEL USING TIME SERIES PREDICTION TECHNIQUES IN MAINTENANCE DECISION MAKING

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USING TIME SERIES PREDICTION TECHNIQUES
IN MAINTENANCE DECISION MAKING**

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**A thesis submitted
in fulfillment of the requirements for the degree of Doctor of Philosophy**

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2014

DECLARATION

I declare that this thesis entitled “A Data-Driven Prognostic Model using Time Series Prediction Techniques in Maintenance Decision Making” is the result of my own research work except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in term of scope and quality for the award of Doctor of Philosophy.

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Date : 11 SEPTEMBER 2014

DEDICATION

To my husband Nirman Ismail, my sons Izwan Iskandar and Iman Idzham, my daughters Izwa Syahirah and Illesya Syafiqah for your ultimate love, understanding and patience.

ABSTRACT

In recent years, current maintenance strategies have extensively evolved in condition-based maintenance solution in order to achieve a near-zero downtime of equipment function. One of these support elements is the use of prognostic. Prognostic has progressed as a specific function over for the last few years. It provides failure prediction and remaining useful lifetime (RUL) estimation of a targeted equipment or component. This estimation is beneficial for production or maintenance people as it allows them to focus on proactive rather than reactive action. While some prognostic models are created based on the historical failure data, others remain as simulation models serving as a pre-exposure effect analysis. Although the concept of a data-driven prognostics model using condition monitoring information has been widely proposed, the validation in predicting the target value continues to be a challenge. In addition, the prognostics have not been applied directly within the maintenance decision making. Hence, the aim of this study is to design a data driven prognostics model that predicts the series of future equipment condition iteratively and allows the process of maintenance decision making to be carried out. The initial phase of this research deals with a conceptual design of data-driven prognostics model. This conceptual design leads to the formulation of a generic data acquisition and time series prediction techniques, which are the key elements to predictive prognostic solution. In this case, there are four techniques have been used and formulated to have better prognostic results namely: Double Exponential Smoothing (DES), Neural Network (NN), Hybrid DES-NN and Enhanced Double Exponential Smoothing (EDES). The intermediate phase of this research involves the development of a computational tool based on the proposed conceptual model. This tool is used for model implementation that uses the experimental data to test the ability of the prognostics model for failure prediction and RUL estimation. It also demonstrates the integration of prognostics model in maintenance decision making. The final phase of this research demonstrates the implementation of the model using industry data. In this phase, the industrial implementation takes into account the performance accuracy to verify the operational framework. The results from the model implementations have shown that the proposed prognostic model can generate the degradation index from the data acquisition, and the formulated EDES can predict RUL estimation consistently. By integrating it with the maintenance cost model, the proposed prognostic model also can perform time-to-maintenance decision. However, the accuracy of the prognostic and maintenance results can be increased with a huge and quality data. In conclusion, this research contributes to the development of data-driven prognostics model based on condition monitoring information using time series prediction techniques to support maintenance decision.

ABSTRAK

Dalam tahun-tahun kebelakangan ini, strategi terkini bagi penyelenggaraan telah meluas berkembang kepada penyelenggaraan berasaskan kondisi peralatan untuk mencapai *downtime* hampir sifar bagi fungsi peralatan. Salah satu daripada elemen-elemen sokongan ialah penggunaan *prognostic*. *Prognostic* telah berkembang sejak beberapa tahun yang lalu sebagai fungsi tertentu untuk menyediakan ramalan tentang kegagalan dan baki anggaran masa hayat (*RUL*) peralatan atau komponen yang disasarkan. Anggaran ini adalah bermanfaat kepada pihak pengeluaran dan penyelenggaraan kerana ia membolehkan mereka melaksanakan tindakan proaktif dan bukan reaktif. Namun, sesetengah model *prognostic* yang telah dicipta hanya berdasarkan data kegagalan terdahulu, yang lain-lain kekal sebagai model simulasi untuk digunakan hanya sebagai pra-analisis. Walaupun konsep model prognostic berdasarkan data kondisi peralatan telah dicadangkan secara meluas, namun pengesahan dalam meramalkan nilai anggaran masih terus menjadi satu cabaran. Di samping itu, *prognostic* masih tidak digunakan secara langsung dalam membuat keputusan penyelenggaraan. Oleh itu, tujuan kajian ini adalah untuk mereka bentuk satu model *prognostic* berasaskan data kondisi untuk meramal siri kondisi peralatan masa depan secara berulang dan membolehkan proses membuat keputusan penyelenggaraan dapat dilaksanakan. Konsep reka bentuk ini membawa kepada pengubalan satu kaedah perolehan data yang umum dan teknik ramalan siri masa sebagai kunci penyelesaian utama untuk sebuah penyelesaian ramalan ini. Dalam kes ini, terdapat empat teknik siri masa telah diguna dan digubal untuk mendapatkan keputusan yang lebih baik dalam membuat ramalan *RUL* iaitu: *Double Exponential Smoothing* (DES), *Neural Network* (NN), *Hybrid DES-NN* dan *Enhanced Double Exponential Smoothing* (EDES). Fasa pertengahan kajian ini melibatkan pembangunan satu alat komputeran berdasarkan konsep model yang telah direkabentuk. Alat ini digunakan untuk memudahkan pelaksanaan model dengan menggunakan data eksperimen untuk menguji keupayaan model prognostic untuk ramalan kegagalan peralatan dan anggaran *RUL*. Ia juga dapat menunjukkan integrasi prognostic model dalam membuat keputusan penyelenggaraan. Fasa akhir kajian ini menumpukan kepada pelaksanaan model menggunakan data industri. Dalam fasa ini, pelaksanaan mengambil kira ketepatan prestasi untuk mengesahkan rangka kerja operasi. Hasil dari kedua-dua pelaksanaan model menunjukkan bahawa model ramalan yang dibangunkan berupaya menghasilkan indeks degradasi peralatan dari kaedah perolehan data, teknik EDES yang digubal dapat meramal anggaran *RUL* secara konsisten. Dengan menyepadukan model kos penyelenggaraan, model *prognostic* yang dicadangkan juga berupaya menentukan masa untuk melaksanakan penyelenggaraan. Walaubagaimanapun, ketepatan keputusan ramalan dan penyelenggaraan masih boleh dipertingkatkan dengan data yang berkualiti dan berkuantiti baik. Kesimpulannya, kajian ini menyumbang kepada pembangunan satu model prognostic berasaskan data kondisi dengan menggunakan pendekatan ramalan siri masa untuk menyokong keputusan penyelenggaraan.

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LIST OF ABBREVIATIONS

ANN or NN	-	Artificial Neural Network
ARMA	-	Auto Regressive Moving Average
ARIMA	-	Auto Regressive Integrated Moving Average
CBM	-	Condition Based Maintenance
CM	-	Condition Monitoring
C_f	-	Cost of Failure maintenance
C_p	-	Cost for Preventive maintenance
CTRM	-	Composites Technology Research Malaysia
DAQ	-	Data Acquisition Card
DES	-	Double Exponential Smoothing
DI	-	Degradation Index
DMG	-	Decision Making Grid
EDES or EDE	-	Enhanced Double Exponential Smoothing
ES	-	Exponential Smoothing
FFNN	-	Feed Forward Neural Network
FL	-	Fuzzy Logic
LR	-	Logistic Regression
MLE	-	Maximum Likelihood Estimation
MSE	-	Mean Squared Error
MMSE	-	Minimum Mean Squared Error
OR	-	Operations Research
PCA	-	Principal Component Analysis
PM	-	Preventive Maintenance
RMSE	-	Root Mean Squared error

RUL	-	Remaining Useful Lifetime
SWOT	-	<i>Strengths, Weakness, Opportunities, and Thread</i>
SES	-	Simple Exponential Smoothing
SSE	-	Sum Squared Error
TTM		Time-to-maintenance

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