A NEURAL NETWORK APPROACH FOR MACHINE BREAKDOWN REPAIR TIME

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Specially dedicated to mom and dad

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ABSTRACT

Research on neural network applications have been carried out very extensively in recent days. The current trends in manufacturing sectors for solving their business operational problems have been very difficult and subjective. Many organizations have used various methods to solve machine breakdown's repair time, either reducing the time taken to repair or eliminate the particular occurrence. The traditional way for solving these machine breakdown issues was to predict the machine breakdown occurrence through preventive maintenance. Hence, in the present study, a neural network method was proposed to optimize the mean repair time for machine breakdown with regression models were evaluated from the trained neurons. The neurons were represented by the samples of repair time of previous years' record of a single machine. The results shows that the set of samples of repair time have critically influenced the optimized mean repair time for the machine. Various methodologies were used by comparing several grouped machine breakdown phenomena which showed more accurate regressions. The use of neural network, in the end of the study, gives significant changes in predicting machine breakdown repair time for the future years.

ABSTRAK

Penyelidikan ke atas aplikasi rangkaian neural telah dijalankan sangat meluas di hari baru-baru ini. Trend semasa dalam sektor pembuatan untuk menyelesaikan masalah perniagaan operasi mereka telah amat sukar dan subjektif. Banyak organisasi telah menggunakan pelbagai kaedah untuk menyelesaikan masa pembaikan kerosakan mesin, sama ada mengurangkan masa yang diambil untuk membaiki atau menghapuskan kejadian tertentu. Cara tradisional untuk menyelesaikan isu-isu kerosakan mesin adalah untuk meramal berlakunya kerosakan mesin melalui penyelenggaraan pencegahan. Oleh itu, dalam kajian ini, kaedah rangkaian neural telah dicadangkan untuk mengoptimumkan masa pembaikan min untuk kerosakan mesin dengan model regresi telah dinilai dari neuron terlatih. Neuron diwakili oleh sampel masa pembaikan rekod tahun-tahun sebelumnya untuk mesin tunggal. Keputusan menunjukkan bahawa set sampel masa pembaikan telah amat mempengaruhi masa pembaikan min yang dioptimumkan bagi mesin. Pelbagai kaedah telah digunakan dengan membandingkan beberapa kerosakan dengan dikumpulkan fenomena kerosakan mesin yang menunjukkan regresi-regresi yang lebih tepat. Penggunaan rangkaian neural, di akhir kajian, memberikan perubahan ketara dalam meramalkan masa membaiki kerosakan mesin untuk tahun-tahun akan datang.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Most manufacturing companies produce products from home appliances to food industry for instance. Before producing actual product, the company practically study or analyse the incoming sales first. The sales quantity for a particular product is then sent to the planning department for scheduling process. Upon complete scheduling, the manufacturing or assembly of product department will follow the planned scheduled accordingly. In the scheduling process, there are several factors that make scheduling tasks become more challenging and tougher for production planners. Though there are many systems to consider these factors and to ease the task of the planners, there are constraints that indirectly cannot be solved. The most frequent scheduling factor is the multiple models that a manufacturing line produces in a day for instance. When there is an existence of multiple model of a product, the schedule is then planned for different models in a day, adjusted according to sales to warehouse requirements.

Nowadays, with customer oriented businesses, manufacturing companies especially the sales section tend to fulfil the customer's needs in means of delivery of the product to them. This commonly can be seen in automotive industries when a car ordered by customer is obtained within 2 weeks. Typical companies may take close to 2 months for order lead time inclusive of manufacturing time from the factory. From this, we can foresee the importance of scheduling tasks for the benefit of sales achievements, delivery lead time, model change planning and perhaps helps the new product line up of certain companies. However, these scheduling processes are not useful if the operations in the factory face many issues on their facilities. The facilities for producing the desired products are very important because failure of operating the facilities in normal condition will affect all the factors mentioned above. This study solely look into facilities breakdown problems and the need of breakdown's repair time to be reduced for obtaining high machine utilization rate. With high machine utilization rate, production processes run smoothly and will be able to achieve sales and profit targets as part of the organizations' desirable goals. In this study, machine breakdown repair time is being analysed.

1.2 Background and Rationale

The scheduling tasks can be made through various systems that many experts have designed and developed through the decades. Scheduling in a typical and small manufacturing factory is performed using simple Excel Worksheet. The rule of thumb for scheduling is supply meets the demands i.e. supply must be equal to demand. Demand from sales section is converted to supply as the output of the product quantity called as finished goods. For bigger manufacturing companies usually uses the similar formulae but with planned quantity of inventory. However, for manufacturing companies that make electrical appliances, automotive, food industries and other industries those indirectly play a dominance role in the consumer’s market uses systems such as CANVAS METAFRAME, Sapphire, Oracle System and other reliable software to make the scheduling tasks easy and fast. Most of these systems’ inherent element is actually using conceptual artificial intelligence. Artificial Intelligence can be simply defined as the study of systems that act in a way that to any observer would appear to be intelligent (Coppin, 2004).

Customer needs have become the main priority for any manufacturing firms. The most critical criteria for a customer are to obtain his/her product within the required or fastest time. This is a major constraints neither the planner nor the shop floor supervisors. They have to complete their work order within the time frame given by the demanding sales. Thus, the multiple model of a product will be automatically factored into the schedule plan. With this, planners need to make many assumptions during making the schedule. They have to factor in the other requirements of other models too. Mixing many models into a production line is rather difficult tasks and requires a lot of brainstorming. The rationale is these planners will make some assumption such as IF THEN rules manually. For instance, Rule 1: IF the line produces 500 sets of model A by 3.00pm for delivery, THEN balance working time of 2 hours can be fitted with another model B which delivery requirement falls on the same day. The main constraint is the quantity of model B that can be produced is 200 sets for 2 hours. Rule 2: IF the model B demand for the day is 150 sets for delivery, THEN rule 1 can be implemented with respect of rule 2 executions. The balance 50 sets of model B becomes an inventory for the day before next delivery. The above rules are just for an example, but in real time, the constraints can be as complicated as producing more than 5 models a day.

1.3 Problem Statement

Production scheduling and it's diagnose towards re-scheduling is performed manually especially and particularly for machine breakdown issue. Typical scheduling is made in Excel worksheet and adjusted manually on the same Excel worksheet. There is no proper method for making schedule automatically thus reducing job of re-scheduling.

The machine breakdown occurrences need justification of recovery solution in term of mean repair time. Apart from that, if machine breakdown occur, the schedule is adjusted manually. Nevertheless, some recovery solutions in term of repair time can be not feasible enough to meet due dates and meeting other requirements in production scheduling.

1.4 Objectives of the Project

1. To train the neurons of repair time samples based on the machine breakdown list.

2. To compute the mean square error (MSE) and regression, R value of the trained neural network.

3. To evaluate and validate the regression of the trained network by creating the regression model and compute the optimized mean repair time for machine breakdown.

1.5 Research Questions

1. How the neurons are being trained and how the samples of machine repair time are taken?
2. How the mean square error (MSE) and regression R value is obtained from the trained network?
3. What is the optimized mean repair time for the breakdown phenomena?

1.6 Scope of Study

The scope of this project is restricted to machine breakdown phenomena as the samples. However, a rather huge sample of data in terms of repair time is taken from a manufacturing company. The sample of repair time is restricted to only one machine which has been operating for more than 25 years. The samples are in range of 21 years where every year, all phenomena that have been recorded with repair time are used in this project for the neural network training.

The MATLAB's Neural Network Toolbox is used throughout the project. In particular, the Neural Network Fitting Tool is used which is a ready-made Graphical User Interface inside the said program. The fitting tool uses the approach of Levenberg-Marquardt back propagation algorithm as a training tool for the neurons. The neurons in this study refer to the samples of repair time. Microsoft Excel is used to assist in sorting out the data based on the required testing, validation and training of the neurons.

The samples are divided into several groups for comparison purposes which are purely based on the type of machine breakdown and its cause-effect interrelation.

1.7 Significance of study

This research is aimed to ease the task of production planners and maintenance team. It can reduce the time taken for a planner to analyse the solutions for recovery time and fit the recovery schedule into the actual dynamic schedule. Planners no longer need to plan how to fit the recovery schedule since this research acquires the help of Artificial Neural Network to make the recovery plan.

Some manufacturing companies tend to conduct meeting to solve machine breakdown problems. Supervisor, maintenance technicians and production planners gather to conclude the best recovery solutions after taking consideration of machine downtime and other considerable factors. But, in certain cases, there will be misunderstanding between these groups of employees. Thus, the new system will be able to reduce meetings between them and indirectly solve the recovery time.

This research upon completion need to be reviewed again and if possible, a Graphical User Interface (GUI) is prepared to ease any end user. Hence, this GUI becomes a product to be targeted to all manufacturing companies. Certain service companies may benefit from this research depending on their business needs.

1.8 Structure of Thesis – Chapters Overview

This thesis shall consist of basic elements of project report. Chapter 1 discusses about the introduction, research objectives, scope of project and the significance of the project. The next Chapter 2 is the literature review of previous researches and projects that related with this thesis. Chapter 3 discusses the steps or methodology of the project. The methodology of this project is based on simulation and testing, thus the final step consists of testing data and its validation. Chapter 4 summarizes the simulation steps upon successful data selection. Chapter 5 consists of types of testing conducted and selected neural network training. The neurons are trained in this chapter based on certain manipulated conditions before training activity. Chapter 6 is the discussion topic on results gained through this project and includes the validation of selected sample data. Besides, various analyses of the results are summarized in this chapter. Chapter 7 concludes the project with recommendations for future work.

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