GENERAL REGRESSION NEURAL NETWORK BASED TIME SERIES MODELLING FOR PREDICTION AND ANALYSIS OF CONSTRUCTION EQUIPMENT MAINTENANCE COSTS

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2014

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General Regression Neural Network Based Time Series Modelling for Prediction and Analysis of Construction Equipment Maintenance Costs

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A Thesis Submitted

In Partial Fulfilment

of the Requirements for the Degree

Master of Philosophy

July 2013

CERTIFICATE OF ORIGINALITY

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Abstract

Construction equipment owners and equipment contractors often face the difficulties of forecasting the behaviour of maintenance cost as breakdown of equipment can come in sudden during its servicing period. This poses an uncertainty to equipment owners that future maintenance costs may have severe discrepancy with the estimated maintenance cost under the routine maintenance schedule. This uncertainty in turn adversely affects the financial management and replacement decision making for construction equipment by the owners. This study, which attempts to provide a better solution to this problem, applies a time series analysis based on General Regression Neural Networks (GRNN) model to address the modelling and prediction of construction equipment maintenance costs. The research covers modelling of both fleet maintenance cost and equipment lifecycle maintenance cost to provide a comprehensive analytical modelling framework for construction equipment maintenance cost problem. The results show that the use of time series approach based on GRNN gives a satisfactory result for maintenance cost modelling and prediction for both fleet maintenance cost and equipment lifecycle maintenance cost with some important implications derived by global sensitivity analysis based on the model. And the use of the GRNN model in optimal replacement model provides a near-optimal timing for equipment replacement.

Acknowledgement

I would like to express my gratitude towards my supervisor, Dr HQ Fan, for his every valuable advice for the research. He always offers new ideas for improving the research, which eventually accomplish this thesis. I also thank Dr Fan for giving me the opportunity for studying this research degree.

I am also full of thankfulness to the research advices and guidance provided by my co-supervisor, Prof YH Chiang, who supports me in every way to improve the research works.

Finally, I am deeply indebted to my family who fully support me. This thesis is a dedication to them.

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1. Introduction

1.1. Overview

Construction equipment maintenance cost is crucial to different parties for the construction industry. First, it forms an important element to budgeting of the construction contractors, especially for those specialized in equipment-intensive construction activities. Construction equipment, with functions of earth moving, roadwork, etc., is subject to various forms of maintenance like condition-based maintenance and fixed-time maintenance, which all accumulate a substantial amount of cost to the company. More or less the same, the equipment rental companies face similar circumstance as the maintenance cost contributes to a large part of operation cost of the company. Second, equipment maintenance cost is essential for resources planning of the company. The maintenance cost dynamics virtually play a large role for optimal decision making for equipment replacement. While it is natural that maintenance cost increases throughout the lifecycle of equipment, when the rise of marginal maintenance cost will offset the marginal revenue and result in negative marginal net revenue of equipment are still essential questions for equipment owners. Thus analysis of the behaviour of maintenance costs of different equipment categories or individual equipment can provide information on determination of optimal equipment replacement timing and future resources allocation.

Traditionally, construction industry practitioners estimate and predict future maintenance cost of various construction equipment based on experience. A lot of related indicators can be taken into consideration by them, including the fuel consumption, machine age, weight, working environment etc. Such judgment based on intuition came from the above indicators could be unreliable. While no consensus of the methodology or systematic approach for prediction are made by practitioners, statistical modelling of construction equipment maintenance cost serves to provide a better and more systematic quantitative approach for prediction of future values.

Previous research in this area, which commonly employed linear regression by ordinary least square method, have been conducted (e.g. Manatakis and Drakatos (1993); Edwards et al. (2000a), (2000b), (2000c); Edwards and Holt (2001); and Gillespie and Hyde (2004)). Apart from these conventional statistical approaches, use of time series approach in this area or related field has been advocated with evidence by prior study. Moore (1976) showed the existence of positive autocorrelation in equipment maintenance cost time series, which demonstrates the existence of influence from past behaviour on future maintenance cost behaviour. And the previous applications of time series method for maintenance cost modelling provide some further insights for development of maintenance cost modelling. For example, Edwards et al. (2000b) employed moving centred average as a time series approach to investigate the construction equipment maintenance cost time series. Zhao et al. (2007) also used an autoregressive moving average model (ARMA), which is a benchmark time series technique developed by Box and Jenkins (1976), to analyse the failures of equipment. All these attempts which successfully analysed the behaviour of equipment performance and maintenance cost showed the plausibility of employment of time series approach on maintenance cost modelling.

While time series analysis has been traditionally conducted using Box-Jenkins Approach, Artificial Neural Networks (ANN) is also recognized to be capable in equipment and plant maintenance cost modelling and analysis. Prior researches have presented the use of ANN in field of modelling of construction equipment maintenance cost and related areas. Edwards et al. (2000a) used multilayer perceptron (MLP) to predict the future values of maintenance cost of construction plants with better performance over other modelling algorithms such as multiple regression. Hong and Pai (2006) modelled and predicted engine reliability by a various forms of models including General Regression Neural Networks (GRNN), Support Vector Machine and ARIMA and compared the performance among them. These prior works serve to demonstrate that the application of neural networks in equipment maintenance cost and related researches provide meaningful results.

Under the insight that the equipment maintenance cost behaviour is influenced by its historical values of maintenance cost (Moore, 1976) and prior studies applying neural networks give encouraging prediction results, the research aims to develop time series models for construction equipment maintenance cost based on GRNN, which is believed to be able to appropriately model the input-output mapping between lagged values of variables and the future maintenance costs. The study includes two main aspects of construction equipment maintenance cost modelling and analysis. The first phase of the study considers the modelling of the equipment fleet maintenance cost time series to examine the lagged relationship of construction equipment maintenance cost. The study also investigates the impact of fuel consumption on maintenance cost modelling by referring to the improvement of modelling ability made by this addition of variable. Apart from formation of models, this study also aims to investigate how the total maintenance cost of construction equipment depends on each of the input variables in the model. A global sensitivity analysis is then conducted on the multivariate GRNN models to examine the sensitivities of each variable included. The second phase of research studies the development of model for individual equipment lifecycle maintenance cost. The phase of study provides important knowledge on role of lifecycle maintenance cost on optimal replacement decision making. The modelling of lifecycle maintenance cost employs the same algorithm with results presented with discussions. The GRNN model developed in this phase will be incorporated into a simple optimal replacement model and this integration will be examined based on how the predictions of lifecycle maintenance cost by GRNN can indicate replacement timing of construction equipment.

1.2. Objectives

In this study, several objectives are aimed as follow:

i. Development of model for construction equipment fleet maintenance cost behaviour that can facilitate financial management for construction equipment owners

ii. Analysis of influences of different parameters on the movement of construction equipment fleet maintenance cost for better understanding of dynamics of fleet maintenance cost

iii. Development of model for construction equipment lifecycle maintenance cost behaviour that can provide vital information for optimal equipment replacement decision making

iv. Investigate the effectiveness of GRNN model for lifecycle maintenance cost for optimal replacement decision making

1.3. Organization of thesis

This thesis is organized as follow: Chapter 1 briefly describes the construction equipment maintenance cost problem with the main difficulty of practitioners in handling the problem and the objectives of this research aimed to fulfil for equipment maintenance cost problem. Chapter 2 focuses on the review of literature related to the scope of this research. It includes the prior works of maintenance cost modelling of construction equipment and related equipment of other industries and optimal equipment replacement approach. This chapter also provides a description of fundamental knowledge about equipment maintenance cost. Chapter 3 covers the General Regression Neural Network (GRNN) in-depth by its structure and statistical meaning in model development. Its implication for application in time series is also discussed. Chapter 4 presents the first phase of the study which develops time series models for fleet maintenance cost based on GRNN and discusses different aspects of the results. It also describes the conventional time series methods and uses these methods for comparison to the GRNN model to investigate the modelling performance of each. It then shows the use of global sensitivity analysis based on GRNN developed for fleet maintenance cost. The results are discussed and interpreted. Chapter 5 covers the development of lifecycle maintenance cost model based on GRNN. The results are illustrated by different statistical methods. This chapter then elaborates the integration of lifecycle maintenance cost GRNN model into an optimal replacement model and illustrates the effectiveness of GRNN model prediction as information for optimal equipment replacement decision making. Chapter 6 concludes the research, with description of limitations and outlines of future works.

2. Literature Review

2.1. Fundamentals of Construction Equipment Maintenance Costs

Maintenance can be defined as any activity, including but not limited to tests, replacements of parts, repairs and measurements, to restore the functional unit to a specified state such that the unit can carry out the required function (General Services Administration, 1991). In general, maintenance activities can be classified into preventive maintenance and corrective maintenance. Preventive maintenance provides suitable measures to equipment before breakdown of equipment in order to prevent the failure or breakdown of the equipment. Corrective maintenance, on the other hand, gives equipment maintenance after breakdown of equipment. It involves repairs and replacements of parts. Both of these maintenance processes contribute to the formation of total maintenance cost, though in different proportion. In sense of maintenance costing, the part of corrective maintenance holds a substantial proportion of total maintenance cost compared to preventive maintenance. In the following, a review on fundamental components of maintenance cost of construction equipment will be conducted.

Edwards et al. (1998) provided a comprehensive review of maintenance management of construction equipment. Equipment maintenance cost can be divided into two parts:

direct and indirect maintenance cost. The direct cost of maintenance for construction equipment involves a variety of components: labour cost, consumables cost, component part cost and overhead cost. The labour cost refers to the direct cost of employment of a recognized technician or professional to perform the required maintenance works. Edwards et al. (1998) suggested that the actual gross wage for the employed is dynamic and is subject to a wide range of variables. For cost of consumables, it includes the costs of some supplementary materials for operation of construction equipment such as engine oil, hydraulic oil and vehicle grease. These kinds of equipment lubricants cost only a very small portion of total maintenance cost and typically rise with size and complexity of machine (Edwards et al., 1998). Regular inspection and replacement of lubricants and grease is very cost-effective in the sense that it also provides important information on how machine is deteriorating as the condition of lubricants reflects the condition of machine under Used Oil Analysis. Component part cost plays a major part for formation of maintenance cost of construction equipment. Edwards et al. (1998) indicates that, using tracked hydraulic excavator as an example, replacement of a small proportion of components inside the machine can almost cost as much as a new machine. Under this example, it reflects that maintenance decision can be uneconomical when the components needed to be repaired or replaced are too much, resulting in an unjustified maintenance decision. Finally, the overhead cost in maintenance management refers to cost of purchasing and operating maintenance facilities. While purchase of maintenance facilities is a sunk cost and does not affect long term maintenance decision, operation cost of facilities incurs a substantial amount of total cost. For small company, the overhead cost is generally smaller as it tends to contract its maintenance activities to specialized maintenance contractors but it can be very high for larger company which carry out in-house maintenance. On the other hand, indirect maintenance cost refers to time cost of maintenance activity. It usually includes monetary return the equipment can otherwise obtain if the maintenance would have not been carried out. This indirect maintenance cost, along with the direct cost, forms the total maintenance cost of a single maintenance activity.

The dynamics of maintenance cost of construction equipment poses a vital criterion for decision of ownership of construction equipment. Generally, maintenance cost rises along the life span of a machine (Edwards et al., 1998). On the other hand, net present value of a machine generally depreciates due to natural deterioration. As such, there will be a point which the maintenance cost exceeds the net present value of equipment, making the ownership of machine unjustifiable. As maintenance cost dynamics of construction equipment is essential to determination of life cycle decision of equipment, an adequate model of maintenance cost formation is crucial to facilitate such a decision. In the following, related methodology of maintenance cost modelling and equipment optimal replacement modelling will be reviewed.

2.2. Prior Works on Equipment Maintenance Cost Modelling

Construction equipment maintenance cost[1] is made of several components including regular maintenance (e.g. refill lubricants and fluids), predictive maintenance and corrective maintenance. Considering equipment maintenance cost constitutes a major fraction of the total life cycle cost of the equipment, a satisfactory model for behaviour of cost is crucial for management of equipment. Therefore, much previous works were developed on modelling the maintenance cost of equipment, both for construction and other industries.

A series of construction equipment maintenance cost modelling has been conducted by Edwards et al. First, Edwards et al. (1999) developed a maintenance cost model for tracked hydraulic excavator based on Used Oil Analysis and altitude towards maintenance management. Their results showed that used oil analysis is able to

[1] While the maintenance cost is divided into direct maintenance cost and indirect maintenance cost as stated above, in the following context of the thesis, maintenance cost refers to the direct maintenance cost, unless indirect maintenance cost is involved in the related context, making the context more understandable.

provide certain degree of prediction accuracy of mechanical faults but the model fails to explain a large proportion of maintenance cost variations and therefore they suggested alternative methodology should be employed for better performance. Second, Edwards et al. (2000c) used multiple regression to model the maintenance cost by incorporating several exogenous inputs including machine weight, type of industry and company attitude towards predictive maintenance. They found that these three are all important and the operator skill is not significant as an explanatory factor. Third, another research conducted by Edwards et al. (2000b) involved combination of time series analysis and cubic equation estimation, in which time is used as independent variable, to model the cumulative construction equipment maintenance cost. Fourth, Edwards et al. (2000a) studied the performance of modelling based on neural networks and multiple regression and revealed that neural networks provide a better performance with smaller variance of residuals. They conclude that both forms of model successfully model and predict the maintenance cost and further suggested the use of NN can provide information on judgment of maintenance policy. Fifth, Edwards and Holt (2001) introduced a stochastic model by using random number technique to predict the cost of next maintenance event for tracked hydraulic excavators. The results suggested that the methodology gives a practical management mechanism for future maintenance costs and resource allocation.

Apart from these studies, some research works have been devoted to construction equipment life cycle and its operation costing. Gillespie and Hyde (2004) conducted a statistical modelling of life cycle cost of heavy equipment, which is composed of labour and parts cost for maintenance and fuel cost for equipment usage. They successfully found that the logarithmic model of life cycle cost as function of fuel cost gives a satisfactory modelling and discovered that machine age is not quite useful in prediction of life cycle cost while with the use of fuel cost for equipment the model fitted the data the best. Matthew and Kennedy (2003) developed a theoretical framework for optimal equipment replacement to achieve a maximum net benefit from the equipment by essentially assuming the failure rate is increasing. Crowder and Lawless (2007) studied distribution and costs of replacement cycle for equipment and investigated scheme for preventive maintenance. Manatakis and Drakatos (1993) proposed a model of change in operating cost as a function of operating hours, engine capacity and machine power of the dump truck. van Noortwijk (2003) presented an explicit formulas for computing the variances of discounted life cycle costs which can be applied on unbounded time horizon for optimal design of maintenance management. Edwards et al. (2002) developed a linear regression model for construction equipment downtime cost by using machine weights as independent variable.

Moreover, maintenance and life cycle cost of equipment from industries other than construction were also investigated and these works provide some useful insight on modelling of construction equipment maintenance cost. Rohani et al. (2011) modelled the repair and maintenance costs for tractor by using neural networks. They employed Declining Learning-Rate Factor algorithm in Back Propagation Learning for Multilayer Perceptron and found that the prediction accuracy is promising and suggested neural networks as a robust tool to model and predict maintenance costs. Popova et al. (2006) presented a multiple regression model for the behaviour of total maintenance cost of nuclear power plant by using variables including the number of previous repairs, level of risk to loss of electrical generation, etc. Jun and Kim (2007) developed a life cycle cost model including modelling of annual maintenance cost of railway system and made use of the model to apply on brake module of the system. Christian and Pandeya (1997) investigated the operation and maintenance costs of facilities in university by using neural networks, regression and random deviation detection method and developed a decision-support system based on the above models for prediction of operation and maintenance costs. Neely and Neathammer (1991) developed various databases for building facilities and applied the databases for analysis of high maintenance cost components and tasks. Li et al. (2009) proposed a generalized partial least square regression model for warship maintenance cost with relatively few samples. Parra et al. (2009) introduced a stochastic model, known as Non-homogeneous Poisson Process, for life cycle cost analysis of industrial equipment with estimation of failure costs. They also provided a decision making tool based on the model for maintenance managers to optimize the life cycle costing.

2.3. Optimal Equipment Replacement Policy and Modelling

This section reviews the prior effort in optimal equipment replacement studies and discusses the approaches of handling maintenance cost in their optimal replacement models. Many of the optimal equipment replacement models are constructed based on maximization of net revenue generated by the equipment. While both revenue and cost of equipment include many components, the approaches for combinations of revenue and cost among different models vary. Bellman (1955), who sets pioneered work in equipment replacement modelling, studied the replacement problem by a return maximization model. The model considers three variables as components of return: Output level, maintenance cost and resale value, in which each of them is assumed to be a function of machine age. Matthew and Kennedy (2003) developed a model for optimal replacement model with only considering residual value of equipment after depreciation and maintenance cost respectively as revenue and cost of equipment. Tanchoco and Leung (1987) proposed a wealth maximization model in which wealth, that is defined as discounted value of total net revenue, generated by the machine depends on the input given by the. The wealth of machine depends on the output value produced, maintenance cost and depreciation rate which the former twos are function of input level. Eilon et al. (1966) developed equipment replacement model which takes more revenue and cost components the equipment faces during its service life into consideration. It includes acquisition cost, resale value, maintenance cost, capital allowance and tax rate. This model provides more consideration on actual revenue and cost that equipment will face in real life such as capital allowance and tax. The design of this model has one distinction to other lifecycle models. It includes acquisition cost in the model which seeks to determine the replacement timing before purchase of the equipment. Thus the model computes the expected average cost to use the equipment before the purchase. The time of minimum expected average cost signifies the optimal replacement time. However, this model neglects the output value produced by equipment which will virtually alter the net revenue dynamics of equipment.

The above optimal replacement models were constructed based on net revenue maximization. Apart from this form of replacement models, there are some that are built by cost minimization. This form of replacement model determines the time when the equipment faces the minimum marginal cost. For example, Hritonenko and Yatsenko (2007) introduced a continuous model for equipment replacement which only takes maintenance cost and purchase price into account. Sebo et al. (2013) conducted an optimal replacement time estimation by developing a function for equipment lifecycle cost. However, for this condition to be equivalent to optimal equipment replacement timing, the cost minimization model is necessary to explicitly or implicitly assume the revenue of equipment is constant throughout its lifecycle. The assumption of constant revenue however neglects the depreciation of equipment which lowers the marginal revenue of equipment and this overlooking may result in a prediction of a longer-than-optimal life for equipment. This poses a severe limitation for application of replacement decision making.

Within the optimal replacement model, maintenance cost dynamics is one of the most complicated components as maintenance cost can be deviated from the planned maintenance cost by a large figure (Eilon et al., 1966). This makes the approaches by optimal replacement models in handling maintenance cost essential for it to be an applicable model and poses necessity to review these approaches for further insights. The modelling for optimal replacement done by prior studies mainly relies on assumptions on failure rate and maintenance cost dynamics. Matthew and Kennedy (2003) developed an optimal replacement strategy based on assumptions of failure rate and the relationship between failure rate and time is assumed to be increasing throughout the lifecycle of equipment and provided a numerical example in which the maintenance cost is a step-wise linear function. Dreyfus (1960) formulated an optimal solution to equipment replacement with postulations on revenue, upkeep and depreciation functions in which the upkeep function is assumed to be increasing through age of equipment. Tanchoco and Leung (1987) gave the same assumption on maintenance cost which is postulated to be monotonically increasing for cost of both labour and maintenance input for reflecting the depreciation of equipment. Love and Guo (1996) conducted a repair-limit analysis by using Weibull distribution for the failure rate in Markovian state-switching process which gives state-dependent failure rates across different states of the Markov decision process. Yatsenko and Hritonenko (2010) described the equipment replacement problem in a continuous-time model and explicitly assumed that maintenance cost increases by a constant factor with increase of one unit of time. Reid and Bradford (1983) studied the optimal replacement for farm tractor and adopted a uniform work hour for a year for calculation of annual maintenance cost. Ye (1990) proposed a replacement model in which the maintenance and operation costs of equipment are under a stochastic process. He assumed these costs recurrently increase through age and then back to a fixed cost after a certain point of time signifying overhaul and maintenance. However, this kind of assumptions for maintenance cost dynamics suffers from the fact that the dynamics of failure rate and its corresponding rate of change in maintenance cost depend a lot on actual operation condition and amount and can vary for different equipment and so the dynamical patterns of actual failure rate. Therefore maintenance cost may differ from what have been assumed. This makes the application of a model using uniform assumption on dynamical pattern of failure rate and maintenance cost of equipment difficult to be applied in every real world problem.

Apart from approach that asserts maintenance cost dynamics to be specific form, some replacement models are built with a separate maintenance cost model that is based on actual data of individual equipment or a group of equipment under similar operation condition for representation of equipment maintenance cost dynamics for optimal replacement modelling. Eilon et al. (1966) employed linear regression for maintenance cost against age of equipment from sample of ten trucks and used the result for optimal replacement modelling. Navon and Maor (1995) studied the optimal fleet size and used actual recorded maintenance cost data to build a linear relationship between age and maintenance cost for optimal size model.

2.4. Summary

This chapter reviews the literature for fundamentals of maintenance cost, maintenance cost modelling and optimal replacement modelling for equipment, including both construction equipment and non-construction equipment. The fundamental knowledge of maintenance activity and its corresponding maintenance cost is firstly illustrated with forms of maintenance and components of maintenance cost described. The prior works of maintenance cost modelling are then reviewed. Several comparisons demonstrate that neural network is a suitable modelling algorithm for maintenance cost problem. The relevant researches also provide important insights for model design. Finally, the efforts on optimal equipment replacement modelling are studied. The models characterize maintenance cost dynamics mainly by making simplistic assumptions that may not be too abstract for real cases. This makes practical application difficult and provides some grounds for a more real-case-adaptive approach towards maintenance cost problem within the optimal replacement model.

3. General Regression Neural Network

3.1. Overview

General Regression Neural Network (GRNN) developed by Specht (Specht, 1991) is used as model for construction equipment maintenance cost in this study. GRNN has shown its wide range application in prediction of equipment-related issues such as engine reliability (Hong & Pai, 2006), internal combustion engine fault diagnosis (Wu & Liu, 2009), bearing failure of a mechanical equipment (Gebraeel et al., 2004), building services fault diagnosis (Lee et al., 2004) and power system fault section estimation (Cardoso et al., 2004). For time series modelling and prediction, its performance has been recognized (Leung et al., 2000). The advantages of using GRNN include its generalization ability and the capability to produce a reasonable regression surface even there are only small number of patterns provided (Specht, 1991), which provides an important edge for conventional construction time series studies which normally do not acquire long series length. This algorithm is also well-known in handling infrequent outliers (Leung et al., 2000), which are normally found in maintenance cost time series. In the following, the mechanism of GRNN will be illustrated.

GRNN is a non-parametric regression surface estimator which requires only one pass computation for each learning event and the training of patterns is parallel in nature. For typical GRNN, it estimates the output from an individual input vector as weighted average of observed outputs in which the weights are derived nonlinearly and non-parametrically from Gaussian radial basis function (RBF) according to both its Euclidean distance from observed input vector as well as the smoothing parameter. Figure 1 demonstrates an example of weighted sum of RBFs. To train the network, an optimal smoothing parameter, or the RBF kernel bandwidth, will be selected through iteration which can optimize the network performance. The form of GRNN equation is:

$$\hat{y} = \frac{\sum_i^n y_i \exp(\frac{-(X - X_i)'(X - X_i)}{2\sigma^2})}{\sum_i^n \exp(\frac{-(X - X_i)'(X - X_i)}{2\sigma^2})} \qquad (1)$$

Where $\hat{y}$ is the estimate of y given X, $(X - X_i)'(X - X_i)$ is Euclidean distance between X and observed input vectors, σ is smoothing parameter and exp(·) is the Gaussian form of radial basis function

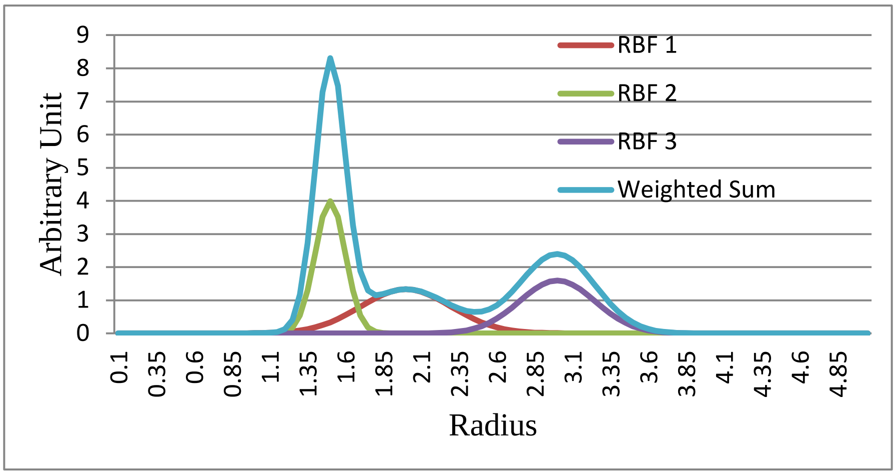

Figure 1 Weighted sum of three radial basis functions with different smoothing parameters

3.2. Architecture of GRNN

A typical GRNN consists of four layers: Input Layer, Pattern Layer, Summation Layer and Output Layer. Each of them carries neurons, the processing units, to perform the computational tasks with the ultimate aim to iteratively train for an optimal smoothing factor for Eq. (1). For the first layer, Input Layer, it receives the data in form that data of each input variables is handled by one and only one input neuron so the number of input variables equals the number of input neurons. For Pattern Layer, after receiving output from Input Layer, each pattern neuron processes the mapping between input vectors and output of one pattern such that the number of pattern neurons equals the number of patterns provided. The mapping of each pattern neuron is governed by a Gaussian radial basis function:

$$\theta_i = \exp\left(\frac{-(X - X_i)'(X - X_i)}{2\sigma^2}\right) \tag{2}$$

Where θ_i is the output from pattern neuron i. $(X - X_i)'(X - X_i)$ is Euclidean distance between X and observed input vectors and σ is smoothing parameter.

Then, Pattern Layer passes the output of Pattern Layer, θ_i, to the Summation Layer. In this layer, there are two kinds of neurons: summation neurons and weighted summation neurons. Their operations are given as follow respectively:

$$S_s = \sum_i \theta_i \tag{3}$$

$$S_w = \sum_i y_i \theta_i \tag{4}$$

Where S_s and S_w are outputs from summation neurons and weighted summation neurons respectively and y_i is the observed output corresponding to X_i. The outputs of this Summation layer, S_s and S_w, form the denominator and numerator of Eq. (1) respectively.

These two values will subsequently be forwarded to the Output Layer, where the neuron(s) in this layer produce(s) the approximation of conditional mean of output by the following operation:

$$y = \frac{S_w}{S_s} \tag{5}$$

Under the operation of four layers of network, it comes up with Eq. (5) which is equivalent to Eq. (1). Through iteration of trials of smoothing parameter with corresponding error obtained, an optimal smoothing parameter can be selected and the regression surface for the problem can be estimated. Figure 2 illustrates the architecture and the training process of GRNN.

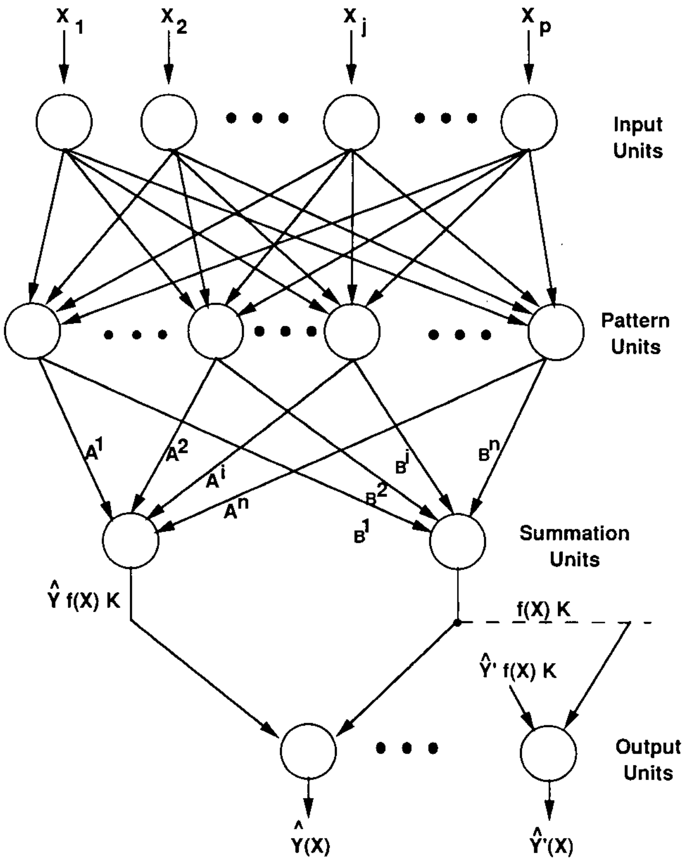

Figure 2 Block diagram of architecture of GRNN (Adopted from D. Specht, "A general regression neural network," IEEE Transactions on Neural Networks, vol. 2, no. 6, pp. 568 - 576, 1991)

3.3. Application of GRNN on Time Series Analysis

3.3.1. Overview of Traditional Time Series Methods

Conventional time series modelling methods mainly rely on the linear models such as ARMA and VAR. Both of them represent a linear combination of past values of observations within the time series. The Box-Jenkins ARMA is in the following form:

$$y_t = C + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (6)$$

Where y_t is the modelled value, ε_t is the error term and ϕ_i and θ_i are the linear autoregressive parameter and moving average parameter respectively. The former part involves past values of times series, known as autoregressive part, examines the lagged relationship between y_t and its previous values and the latter involves the error terms, known as moving average part, reflecting the relationship between y_t and the lagged error terms.

And simple VAR is expressed by:

$$Y_t = C + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t \quad (7)$$

Where Y_t is a $k \times 1$ vector which contains k observations at time t of k time series, ε_t is the error term and ϕ_i is the linear autoregressive parameter. Under this form, VAR directly captures the linear relationships of Y_t with the k time series as well as earlier observations within each time series.

To implement these traditional models, several steps are required for identification of nature of time series being modelled and the structure of the models. Firstly, one important criterion is to ensure the time series being modelled is stationary. The conventional test for existence of unit root is by Augmented Dickey-Fuller Test (ADF) (Dickey and Fuller, 1979). ADF examines the existence of unit root by estimating a linear model involving first differenced value as modelled value and value of time series at time t-1 and previous first differenced values as input variables. Then it involves a statistical hypothesis testing which its ADF statistics measures the estimated coefficient for value at time t-1 over its standard error. Usually this value is a negative number. And more negative this number is more likely the hypothesis of existence of unit root is rejected. If the times series is tested to be non-stationary, k number of differencing is required if there are k unit root(s) existed and the order of integration is expressed as I(k).

For multivariate time series model VAR, the multiple time series in the model need to be tested for cointegration apart from stationarity of individual time series. Cointegration of two or more time series means that the order of integration of linear combination of these time series is lower than order of integration of each of them. To test for cointegration, the Johansen procedure (1988) is one of the most common methods to use. Comprehensive review of Johansen procedure can be referred to Johnes (2000). Johansen procedure provides two likelihood ratio tests as trace test and maximum eigenvalue test. Both of them involves hypothesis testing which examines the number of cointegrating vector that indicates the number of cointegrated time series in the model. If there is cointegrating relationship is not found among the time series in the model, Simple VAR can be applied on the time series studied. If otherwise, Vector Error Correction Model or Cointegrated VAR shall be used instead of the simple VAR.

To identify the suitable structure of ARMA and VAR model, which is their respective autoregressive order and moving average order (for ARMA only), some information criteria are commonly used in the mean of iteratively testing the possible structure of time series models for justification. For example, Akaike Information Criterion (AIC) (Akaike, 1974), derived from information entropy, measures the accuracy of candidate model forms and simultaneously includes a penalty term which is increasing with number of parameters included. AIC is given by:

$$\mathrm{AIC} = 2\mathrm{k} - 2\ln(\mathrm{L}) \tag{8}$$

Where k is the number of parameters and L is the maximum likelihood of the candidate model form. The maximum likelihood can be approximated by the following expression (Chatfield, 2001):

$$N\ln\left(\frac{S}{N}\right) \quad (9)$$

Where N is number of observations and S is the residual sum of squares. The minimum value of AIC from the candidate model forms gives the most suitable structure for ARMA and VAR models.

Based on the structure of these traditional time series models, the mechanism of them maps the past behaviour of a time series to future behaviour linearly. This linear algorithm may not suit the nature of construction equipment maintenance cost dynamics as prior works have suggested that problems of equipment maintenance are characterized by nonlinearity (Hartl (1983); Wang and Pham (1999); van der Weide and Pandey (2011); Boyles et al. (2010)). Therefore, alternative algorithm that can handle the nonlinearity of system should be considered.

3.3.2. GRNN Approach in Time Series Study

Following a review on the traditional time series approaches, this section illustrates how GRNN can be used in time series study and the traditional methods provide information for GRNN model design. The mechanism of General Regression Neural Networks (GRNN) can be summarized as a memory-based network algorithm that estimates an output for an input pattern as a weighted average of outputs of other input patterns in which the weights are determined exponentially based on the Euclidean Distances from the concerned input pattern and smoothing parameter. On the other hand, time series approach is a modelling method that models and predicts the future value(s) of time series by the past values of the time series. The dataset of time series model conventionally contains n overlapping segments of time series which the output for each is immediate next value of the segment and the model makes its computation to optimize the predicted n values compared to the actual values for n segments of time series. Then, for the algorithm of GRNN to be used in time series study, the mechanism is that the algorithm, in parallel, computes the Euclidean distances between the concerned segment of time series and all other segments of the same time series. Next the Euclidean distances from various input patterns, divided by the trained smoothing parameter, will be computed as weights and the weights will be subsequently used for weighted average of all observed outputs. This weight average is the estimated output for the concerned segment of time series. This mechanism, generically, means that GRNN estimates the output for a time series based on the Euclidean Distance between the concerned segment of time series and other segments. For closer one segment is, its output will be weighted more, vice versa. Thus for a segment closer to the concerned segment of time series, the predicted output tends to be similar to observed output from that segment. Also, smoothing parameter determines the weighting and influences the smoothness of function. Under a smaller smoothing parameter, then weights will drop faster from closer patterns to farther patterns than under a larger smoothing parameter. By training of GRNN for time series study, it will iteratively select an optimal smoothing parameter to map the past values of time series and the estimated value(s) and adapt to structure of time series such as noisy or wildly fluctuating.

Based on this mechanism, the edges of using GRNN approach for time series analysis are (1) by training of GRNN, it enables to obtain a global minimum of error surface (Pal & Deswal, 2008) and form an optimal regression surface for mapping of past values of time series and future value while Autoregressive Integrated Moving Average (ARIMA) optimized by Conditioned Least Square may converge to local minima; (2) even the time series is noisy (which may be common for maintenance cost time series or related time series), GRNN is capable of forming a reasonable regression surface as large smoothing parameter can be selected for smoothing out the noisy values of the time series (Specht, 1991) while conventional linear time series methods like ARIMA may model the time series together with noise within the time series and alter the optimal solution; (3) The regression surface formed by GRNN is nonlinear which gives an important edge to conventional linear time series method.

While conventional time series methods have been employed in equipment maintenance cost time series or related time series analysis (For example, Edwards et al. (2000b) made use of moving centred average to analyse the construction equipment maintenance cost time series; Zhao et al. (2007) conducted an autoregressive moving average model (ARMA) to model the equipment; Durango-Cohen (2007) adopted autoregressive moving average with exogenous input model (ARMAX) to model the behaviour of transportation facilities), based on this above mechanism with a number of advantages over traditional methods, GRNN provides a legitimate algorithm for time series study for construction equipment maintenance cost modelling. Nevertheless traditional methods still provide some important information on model design and development of GRNN time series model. Stationarity test like ADF test can examine whether the joint probability distribution of time series is constant over time. If the time series is not stationary, the GRNN model may not be able to map the dynamical patterns it should as the mean and variance of time series are changing over time. For similar dynamical patterns with different means on two different periods of time, when modelling output of each, GRNN may weigh output of another as a small value because the Euclidean distance is large as the mean difference is large even these two patterns are supposed to be useful to each other in determining outputs for each of them as they are similar. In this case, a differenced time series will provide a better representation of time series for GRNN model as the above issue will be greatly alleviated. Also, in determination of lag length for GRNN time series model, optimal AIC selected from a range of lag length in traditional methods provides essential reference of lag length selection for developing GRNN model.

3.4. Summary

This chapter describes the algorithm and structure of General Regression Neural Network (GRNN) and its application in time series study and analysis. GRNN, as a nonlinear regression surface estimator, determines the output based on Euclidean Distances from its input pattern to other input patterns as well as the optimized smoothing parameter. This mechanism gives some essential advantages for GRNN to be employed in time series study. In the following chapters, time series approach based on GRNN will be adopted for construction equipment maintenance cost time series modelling and analysis.

4. Construction Equipment Fleet Maintenance Cost Modelling

4.1. Introduction

This chapter presents the methodology for construction equipment fleet maintenance cost modelling and analysis. The modelling of fleet maintenance cost provides equipment owners with vital information of aggregate maintenance cost of different equipment which essentially facilitates the financial management for the fleet. The modelling algorithm for construction equipment fleet maintenance cost time series is a time series analysis based on General Regression Neural Networks. The modelling of both univariate and multivariate (with time series of fuel consumption of equipment as additional input parameters) time series modelling will be employed by algorithm of GRNN. The results will be discussed and their performance will be compared with traditional time series methods: univariate Autoregressive Integrated Moving Average (ARIMA) and multivariate Vector Autoregressive Regression respectively. Then the research also investigates the influences of different input parameters including the past maintenance costs on the future fleet maintenance cost. This study adopts Latin-Hypercube One-Factor-At-a-Time Sensitivity Analysis (LH-OAT) to analyse this multivariate GRNN model. Relevant reviews on the sensitivity analysis will be provided. Results of sensitivity analysis will be interpreted with possible implications for improvement of financial management and resources allocation for construction equipment owners.

4.2. The GRNN Based Time Series Models

4.2.1. Data

The data for construction equipment maintenance cost modelling are from a Canadian road-building contractor's maintenance database shared across different operational divisions since 1998. The database provides raw data of monthly total maintenance cost of equipment for modelling. The total maintenance cost is taken as the sum of preventive maintenance cost, work order maintenance cost and running repair cost in which all these threes include their respective labour cost and parts cost. The major part of the total maintenance cost comes from the running repair cost, which generally accounts for more than 90% of the sum, while preventive maintenance cost and work order maintenance cost constitutes the remaining. In each maintenance event, on average, parts cost is about two to three times of the labour cost. Apart from the total maintenance cost, the database contains additional information of fuel consumptions of the construction equipment. The maintenance cost and fuel consumption data of every equipment provided by the database for each month can be either aggregated or averaged to form a time series representing the fleet maintenance cost and fuel consumption dynamics. Figure 3 illustrates the behaviours of maintenance cost time series and fuel consumption time series respectively representing the aggregated monthly maintenance cost and fuel consumption data of a sample operational division fleet. Maintenance cost time series of two operational divisions' fleet which contains all types of equipment (Fleets of Division A and B) are provided by the database. Apart from study of fleet at divisional level, this research attempts to model and analyse the maintenance cost of fleet made of a single equipment category. The aim of study of this equipment group is to investigate the unique property of maintenance cost dynamics for the category and examine whether the same modelling methodology can be applied on predicting individual equipment category fleet for more flexible construction equipment management. In accordance, maintenance cost time series of fleet made of a single equipment category is extracted in which the equipment category is dump truck (10 wheels). Therefore this research models the maintenance cost behaviour of one individual equipment category fleet and two divisional fleets: the former is comprised of the same type of equipment in each fleet, while the latter constitutes mixed types of equipment in each operational division. For fleets made of individual equipment categories, average maintenance cost time series is modelled in this study while total maintenance cost time series is modelled for divisional equipment fleets.

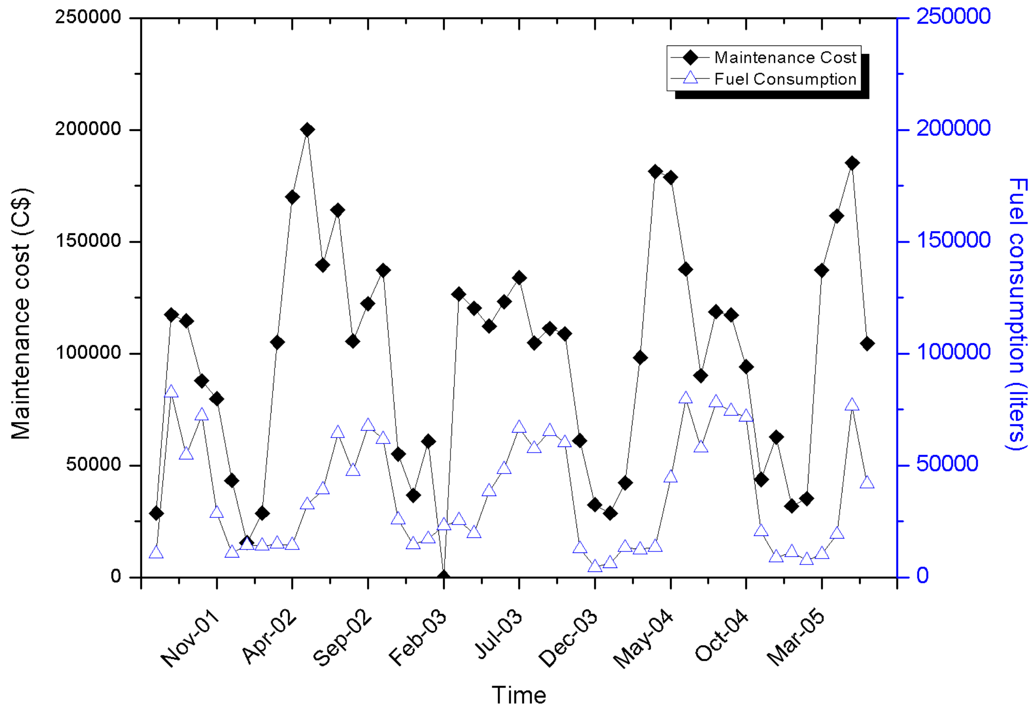

Figure 3 Behaviours of maintenance cost and fuel consumption of a sample fleet

4.2.2. Time Series Models Development by GRNN and traditional methods

This phase of study on time series modelling of fleet maintenance cost examines how GRNN performs for the modelling and uses traditional time series methods as reference for comparison. In the following the procedure of model design and development of both GRNN and traditional methods (ARIMA and VAR) will be presented.

4.2.2.1. Stationarity Test

This study applies Augmented Dickey-Fuller Test (ADF), as described earlier, to examine the existence of unit root(s) in the fleet maintenance cost and fuel consumption time series. The lag length used in the ADF test is determined by Akaike's Information Criterion. Table 1 shows the results of t-statistic of the three maintenance cost time series and their corresponding fuel consumption time series.

Table 1 Unit root test results for maintenance and fuel consumption time series

Group	ADF	p-value
Dump truck fleet maintenance cost ($)	-4.322992	0.001210
Division A fleet maintenance cost ($)	-4.569016	0.000771
Division B fleet maintenance cost ($)	-3.874631	0.004439
Dump truck fleet fuel consumption (litres)	-3.842971	0.022752
Division A fleet fuel consumption (litres)	-4.516352	0.004800
Division B fleet fuel consumption (litres)	-4.124388	0.002175

Notes: The p-value is computed under the algorithm of MacKinnon (1996) one-sided p-values

The results show that all the fleet maintenance cost time series included in this study have no unit roots as the p-values are all smaller than 0.05. In accordance no differencing or detrending are required to transform the time series.

4.2.2.2. Univariate Time Series Modeling

For univariate models for construction equipment maintenance cost, ARMA and GRNN are used and their respective lag orders are determined such that the lagged orders are sufficient to reflect the influence from earlier observations.

For ARMA, both autoregressive and moving average order have to be determined. AIC is used in this study for lag determination. For autoregressive order p and moving average order q, the maximum of both is set to 12 (one year), i.e., $0 \leq p \geq 12$ and $0 \leq q \geq 12$. Each combination of p and q for ARMA will be tested under AIC and the model with a particular combination which scores the smallest value of AIC is selected as the most suitable model structure for ARMA for maintenance cost modelling. For GRNN, the selection of lag follows the autoregressive order selected by AIC. Table 2 summarizes autoregressive and moving average orders for ARMA models and the lag length for GRNN models respectively.

Table 2 Autoregressive and moving orders for ARMA and lag length for GRNN for univariate approach

Group	ARMA		GRNN
	Autoregressive order	Moving average order	Lag length
Dump truck fleet	5	12	5
Division A fleet	5	12	5
Division B fleet	8	12	8

4.2.2.3. Multivariate Time Series Modelling with Fuel Consumption

Apart from the lagged relationship from the concerned time series, other factors are considered as exerting important influence on the determination of future values of construction equipment maintenance cost. Gillespie and Hyde (2004) showed that the fuel expense is crucial to the modelling of the life cycle cost of heavy equipment. However, one drawback of using fuel expense as exogenous input is that the fuel expense is very likely to fluctuate in a similar manner as the crude oil price such that the fuel expense may be unsatisfactory to reflect the exact fuel consumption and in turn the amount of equipment usage. In this study, instead of fuel expense, fuel consumption time series (in litres) is employed to facilitate the modelling of construction equipment maintenance cost in which GRNN and VAR are used for multivariate time series modelling.

As all the maintenance cost and fuel consumption time series are stationary determined by ADF test, the long term dynamics of time series can be maintained. In this case, no cointegration test should be conducted. This result indicates that simple VAR is sufficient to model the three pairs of time series.

Similar to the procedure for lag determination in univariate approach, the autoregressive order of VAR is determined by using AIC, with p ranged from 0 to 12. For GRNN, as for VAR, a uniform lag length will be determined for both maintenance cost and fuel consumption time series and this lag length follows the autoregressive order of VAR. Table 3 summarizes autoregressive order for ARMA model and the lag length for GRNN model respectively.

Table 3 Autoregressive order for VAR and lag length for GRNN for multivariate approach

Time series	VAR	GRNN
	Autoregressive order	Lag length
Dump truck fleet	3	3
Division A fleet	10	10
Division B fleet	6	6

4.2.2.4. Model Validation

To validate the performance and provide proxies to compare the performance of different time series models employed in this study, twelve out-of-sample values, representing maintenance cost of 12 months ahead of time, is predicted and validated by measuring the Mean Absolute Percentage Error (MAPE) of the twelve out-of-sample series using the predicted values and the actual values. This measure describes the capability of the models on the maintenance costs of different equipment groups with a lower value implying a better model with smaller deviations between the predicted values and actual values of time series.

For univariate ARMA, multivariate VAR and GRNN, one-step-ahead approach is used for prediction, i.e., the predicted value of each out-of-sample prediction result will be used as input for next prediction step; for multivariate GRNN, similar approach is used in which the predicted value of each out-of-sample predicted result will be also used as input for next prediction step while a separate optimal ARMA developed based on fuel consumption data in the training set and selected by lowest AIC, from $p, q \in (1,2,\cdots,12)$ where p and q are autoregressive order and moving average order respectively, is used to predict the values of fuel consumption for validation set such that the model can predict the maintenance cost dynamics of 12 months completely ex-ante. Table 4 shows the autoregressive order and moving average order of optimal ARMA for fuel consumption prediction which is to be used in validation set of multivariate GRNN maintenance cost models for three fleets.

Table 4 Autoregressive order and moving average order for three optimal ARMA models of fuel consumption

Time series	Autoregressive order (p)	Moving Average order (q)
Dump truck fleet	10	2
Division A fleet	1	1
Division B fleet	2	2

4.2.3. Results

4.2.3.1. Comparison of ARIMA, VAR and GRNN models

Table 5 summarizes the results of Mean Absolute Percentage Error (MAPE) measured on the three univariate and multivariate models for construction equipment fleet maintenance cost prediction. Figure 4 to Figure 6 show the prediction results compared to the actual maintenance cost time series. Overall, the three models predict the three time series satisfactorily, with maximum average MAPE to be 24.92% from univariate GRNN and minimum to be 21.08% from multivariate GRNN. These results imply that though with different accuracies, the three time series models can adequately predict the behaviour of construction equipment maintenance cost time series. And the results suggest that the use of multivariate GRNN with inputs of both the maintenance cost and the fuel consumption time series provides the best model for modelling of construction equipment maintenance cost.

Table 5 Prediction performance matrix of three models for three equipment maintenance cost time series

$MAPE$	ARMA	VAR	Univariate GRNN	Multivariate GRNN
Dump truck category cost	27.65%	27.46%	25.43%	16.68%
Fleet A maintenance cost	22.61%	17.31%	24.56%	22.88%
Fleet B maintenance cost	22.69%	23.42%	24.78%	23.67%
Average	24.32%	22.73%	24.92%	21.08%

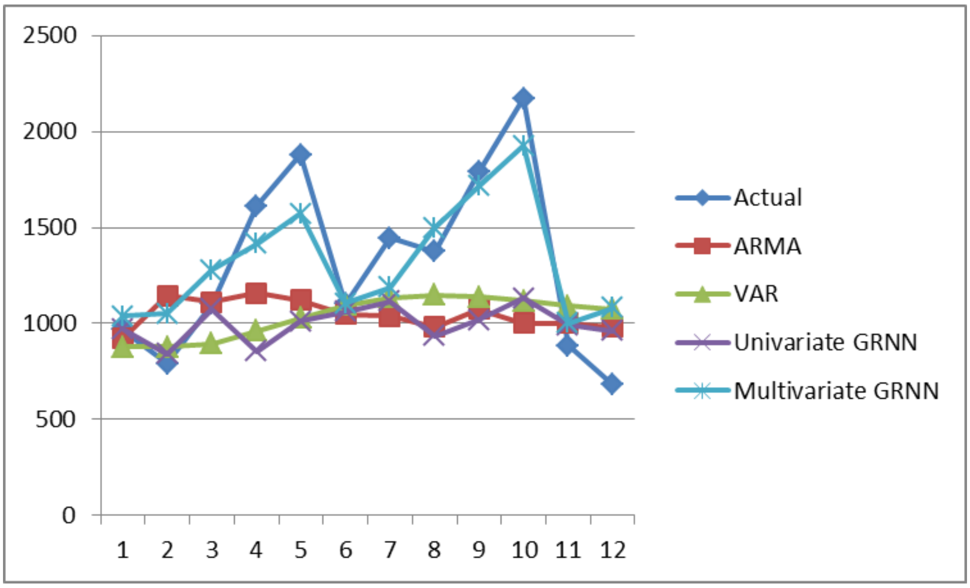

Figure 4 Prediction performance of different models for Dump Truck Fleet maintenance cost

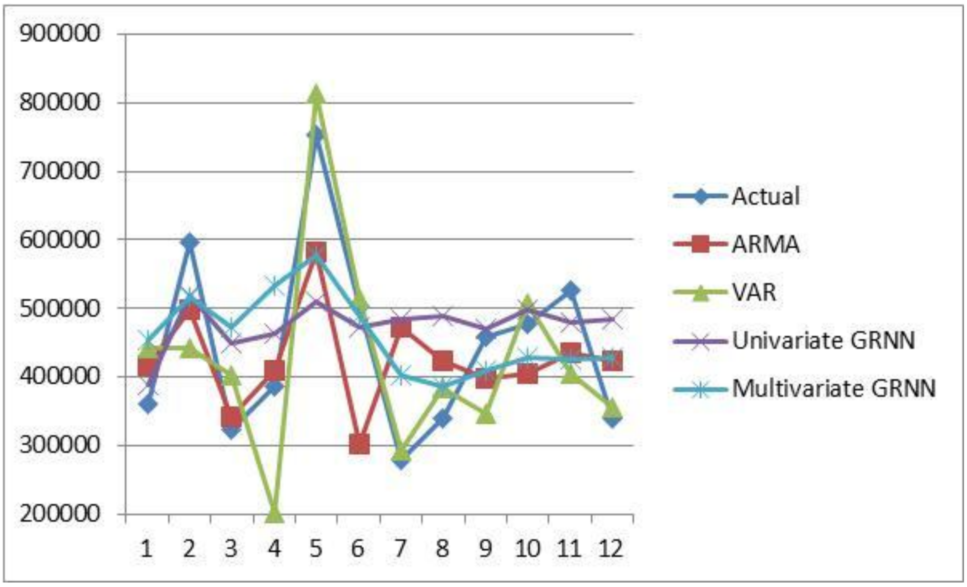

Figure 5 Prediction performance of different models for Division A Fleet maintenance cost

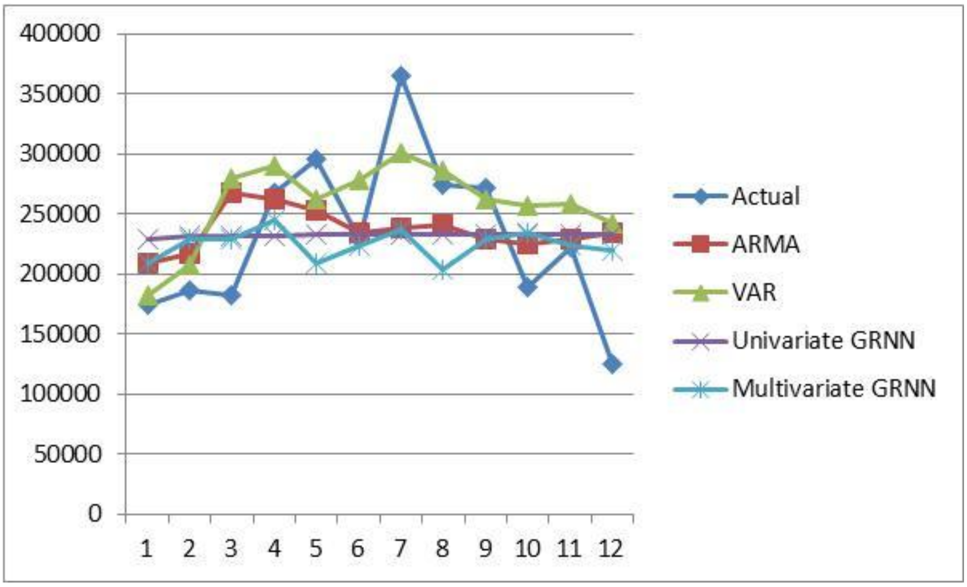

Figure 6 Prediction performance of different models for Division B Fleet maintenance cost

Another important implication from the result is that traditional and neural network approach for time series modelling has different suitability towards univariate and multivariate approaches. For univariate approach, ARMA performs similar to GRNN while for multivariate approach, GRNN gives a better prediction result than VAR. This implies that for univariate approach neural network does not outperform the traditional linear model but it does for multivariate approach. An explanation for this phenomenon is that for univariate approach a linear and simpler model is sufficient to map the lagged relationship of a time series, however for multivariate modelling, a nonlinear network-like learning algorithm is needed to adequately and adaptively estimate the complex time series structure.

4.2.3.2. The Effect of Fuel Consumption on Time Series Modelling

Fuel consumption is assumed to be a good proxy for operation duration and intensity of the construction equipment which in turn affects their deterioration rate and maintenance costs. The addition of fuel consumption time series as an explanatory variable in the models has been found to be significant in construction equipment maintenance cost modelling. However, in this study, the effect of this addition is only significant for individual equipment categories fleet (dump truck) but it does not provide significant improvement for modelling of divisional fleet maintenance cost. See Table 6 for a comparison of average MAPE on equipment fleet comprised of the same types of equipment and divisional fleets comprised of mixed types of equipment.

For individual equipment categories fleet, univariate GRNN only scores MAPE of 25.43% while for multivariate GRNN, its MAPE significantly improves to 16.68%. On the other hand, for prediction at the divisional fleet level, the values of MAPE are observed with minor difference, showing that for prediction of divisional fleet maintenance costs, addition of fuel consumption data does not result in a significant improvement on the modelling performance. The reason behind this finding can be explained by the fact that different equipment categories have different deterioration rate and level of fuel consumption within similar operation time. For individual equipment category fleet, the amount of fuel consumption can be a useful indicator on equipment tear and wear, and subsequently on the required levels of equipment maintenance and repair. For divisional fleet comprised of different types of equipment, some types of equipment are more sensitive to intensive operations in tear and wear than other types, and some equipment types are more fuel-consuming than others. Therefore for divisional fleet cost modelling, the fuel consumption provides very limited information on equipment cost variations. As the amount of fuel consumption is closely related to the workload of the equipment, which is in turn related to the nature and scale of the jobsite to which the equipment is allocated, the fuel consumption of construction equipment can be reasonably estimated during the planning period. Therefore it is both reasonable and practical to incorporate fuel consumption of equipment in a time series model, especially the maintenance cost of equipment categories, to account for the amount of work the equipment is expected to carry out.

Table 6 Average $MAPE$ of prediction results on individual equipment category fleet (dump truck) and divisional fleet (Division A and B) maintenance cost

$MAPE$	ARMA	VAR	Univariate GRNN	Multivariate GRNN
Individual Category	27.65%	27.46%	25.43%	16.68%
Divisional fleet	22.65%	20.37%	24.67%	23.28%

However, the above effect does not hold for traditional linear time series model. Chatfield (2001) underlined that while VAR may better fit the training data than ARMA, it may not predict better than ARMA. The reason of which traditional linear time series method may not model the behaviours of multiple time series is that parameter uncertainty is increased with more input parameters incorporated in the model (Chatfield, 2001) and thus the prediction performance is affected. Also, the linear multivariate approach has more opportunity to over-fit the time series by modelling the noise and outliers (Chatfield, 2001). This sufficiently leads to the result in this study that VAR fails to adequately model the behaviours of both maintenance cost and fuel consumption dynamics and further demonstrate that nonlinear network form of model is a better alternative towards multivariate time series approach for construction equipment maintenance cost modelling.

4.3. Sensitivity Analysis

4.3.1. Latin-Hypercube One-Factor-At-a-Time Sensitivity Analysis (LH-OAT)

In this study, the Latin Hypercube One-Factor-At-A-Time Method (LH-OAT), developed by van Griensven et al. (2006) is employed to perform sensitivity analysis. The combination of Latin Hypercube Sampling and One-Factor-At-A-Time Design enables the sensitivity analysis to a near-global measure of sensitivity without excessive computation necessary to ensure the near-global characteristics held. This method provides a distinct edge over the local methods. While local methods only covers a subset of the whole input parameter space, global methods can sample a parameter set which covers the entire parameter space. Thus local methods only take care of local sensitivity and possibly misjudge the true sensitivity if the model is nonlinear (Saltelli et al., 2000). A global sensitivity analysis enables the analysis to examine the general effects of variations of input parameters to output even the relationship between input and output is nonlinear (Saltelli et al., 2000). Apart from having the advantage that makes the analysis cover the whole parameter space, LH-OAT method also suits General Regression Neural Networks to perform sensitivity analysis. As GRNN estimates the output for a pattern vector as a weighted average of all observed outputs in the training set with each weight based on the Euclidean Distance from that pattern, a conventional sensitivity analysis which uses the known data or training patterns for perturbation could underestimate the sensitivity[2]. For LH-OAT method, it generates a completely new sample to the model which can solve the problem of sensitivity underestimation.

Latin-Hypercube sampling is one form of stratified sampling methods. LH divides the range of each input parameter x_i, $i = 1, \dots, P$ into N intervals with each interval having equal probability of occurrence $\frac{1}{N}$. Inside each interval one observation is generated randomly. Accordingly, there are N non-overlapping observations for each of input parameters. Then, for input parameter x_1, one observation is randomly selected from N observations and is matched with one observation of x_2 which is also randomly selected from N observations for x_2, and so on until x_P. This combination of P observations forms one LH point. After generating first LH point, one of the remaining observations is randomly selected from N observations for x_1

[2] If the known pattern for sensitivity analysis is perturbed by a small fraction, it will make the perturbed pattern having a minute Euclidean Distance to the original pattern and GRNN will weigh the output of the original pattern exponentially high and output of other patterns exponentially low which results in the output for perturbed pattern almost identical to the output for the original pattern and underestimates the sensitivity.

and is matched with one of the remaining observations of x_2 and so on until x_P. This process loops for N times and eventually N LH points are generated. By this method, the entire input space is covered for sensitivity analysis.

The N LH points are then used for one-factor-at-a-time sensitivity analysis (OAT). Standard OAT design performs identically as Finite-Difference Approximation. In this design, the effect of varying the values of each input parameter is carried out in turn, keeping other parameters constant (or ceteris paribus) (Daniel, 1973). OAT makes use of the Latin Hypercube points and perturbs each Latin Hypercube point by a designated fraction. For a model with P parameters, then by OAT, P times of perturbation are required to carry out the whole sensitivity analysis procedure. Together with the model run with non-perturbed parameter values, for each LH point, it requires $P+1$ model runs. It in turn means the whole LH-OAT sensitivity analysis with N LH points requires $N \times (P+1)$ model runs. For each parameter x_i, a partial sensitivity for each LH point j is calculated. The sensitivity for each parameter is then the average of the N partial sensitivities.

Interval	x_1	x_2	x_3
1	100	400	700
2	200	500	800
3	300	600	900

LH Point	x_1	x_2	x_3
1	300	500	700
2	200	600	900
3	100	400	800

Figure 7 Procedure of generation of random sample and LH points: (Left) Generation of random sample points within each interval; (Right) Generation of LH Points which contains sample points of different parameters from different intervals

LH-OAT sensitivity analysis is applied on Multivariate GRNN models. For each parameter x_i, a partial sensitivity for each LH point j, which is derived from the sensitivity calculation developed by van Griensven et al. (2006) to allow negative sensitivity, is defined as follow:

$$S_{i,j} = \frac{100 \times \dfrac{f(x_1, \dots, x_i \times (1 + f_i), \dots, x_n) - (f(x_1, \dots, x_i, \dots, x_n)}{[f(x_1, \dots, x_i \times (1 + f_i), \dots, x_n) + (f(x_1, \dots, x_i, \dots, x_n)]/2}}{P} \quad (10)$$

Where $f(x)$ is the model, P is the designated fraction for perturbation. The sensitivity for each parameter is then the average of the N partial sensitivities.

In this study, P is set as 0.2 and N is set as 100 to ensure that the interval is sufficiently small for the analysis to cover the full range of parameter space.

The LH-OAT sensitivity analysis in this study not only determines sensitivity of lagged maintenance cost and lagged fuel consumption but also identifies the differences of sensitivities of different lags of two parameters. In addition, the aggregate absolute sensitivity of all lagged maintenance costs and all lagged fuel consumptions will also be compared. The results of sensitivity analysis here serve to assist the decision making of the practitioners in the equipment maintenance industry.

4.3.2. Results of LH-OAT

4.3.2.1. The Effects of Parameters to Future Maintenance Cost

Figure 8 to Figure 10 illustrate the sensitivities of different parameters of maintenance cost models for Division A fleet, Division B fleet, dump truck fleet respectively.

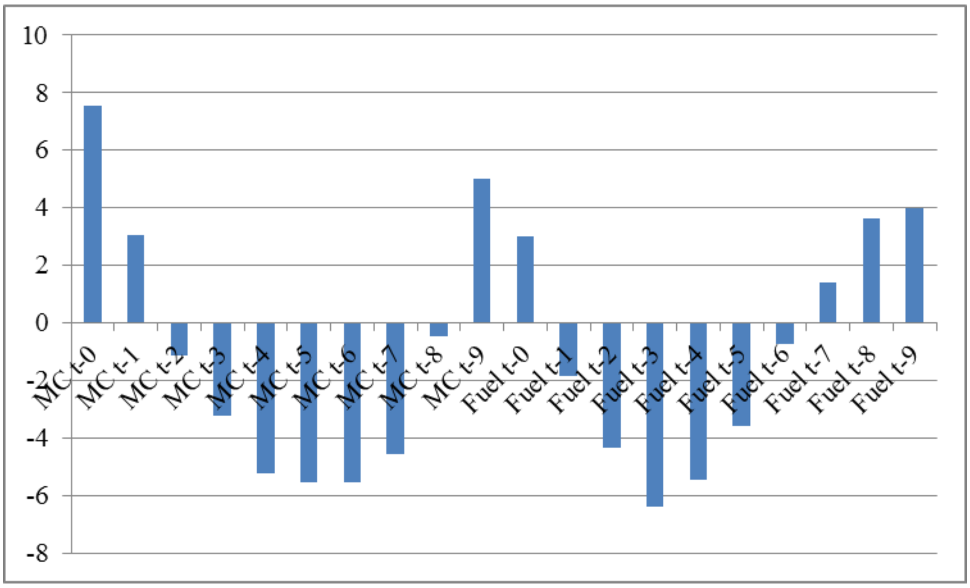

Figure 8 Sensitivities of various parameters of model for Division A Fleet

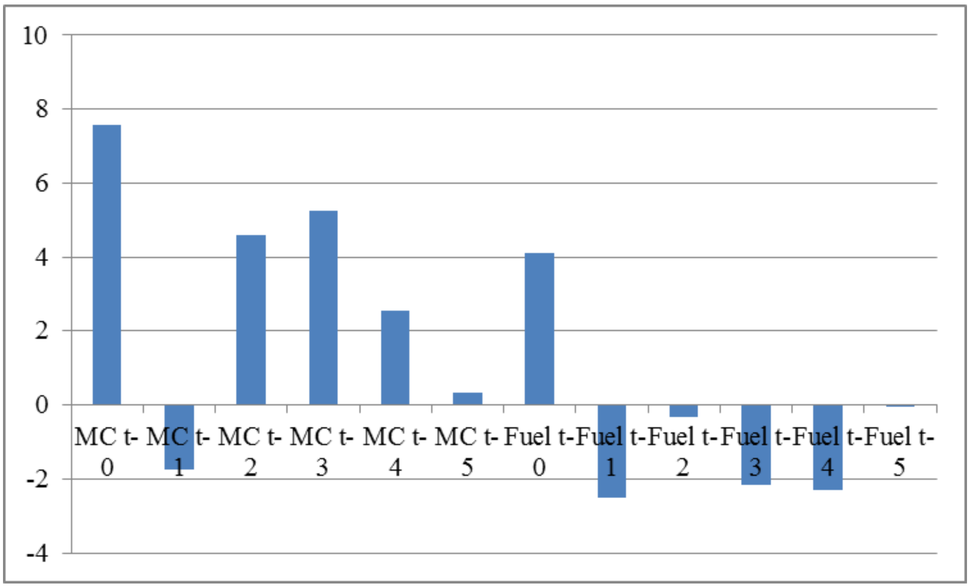

Figure 9 Sensitivities of various parameters of model for Division B Fleet

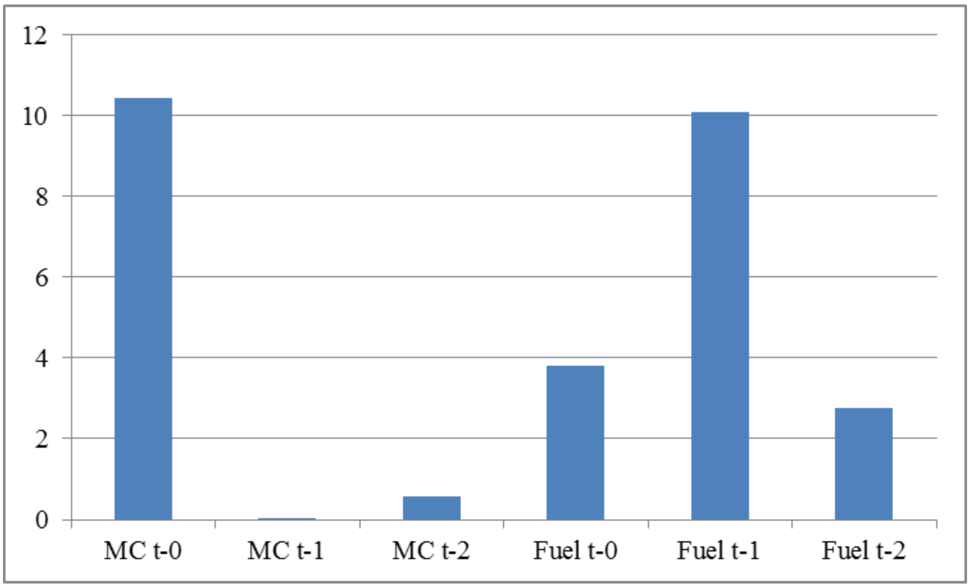

Figure 10 Sensitivities of various parameters of model for Dump Truck Fleet

The results of LH-OAT sensitivity analysis provide some important implications for equipment fleet management and resources allocation. For the sensitivities of past maintenance cost, one universal implication for three fleets with different mixture of types of equipment is that the sensitivities of past maintenance costs decay very quickly with increase of lag. While it is a norm that impact of past values in time series decays over time, the sensitivities for past maintenance cost for the three model decay exponentially rather than a slow decay to zero. For model for Division A fleet, the sensitivities of lagged maintenance cost behave in a U-shape. The sensitivities decay rapidly with increase of lags for t-0 to t-6 and rises back to positive for the rest of the lags. Similarly for Division B Fleet model, the sensitivities decay exponentially as well and at t-5 the sensitivity decreases to nearly zero. Regarding the Dump Truck

Fleet model, the sensitivities essentially drop to zero immediately starting from time at t-1, which shows that the influences from past maintenance cost diminish rapidly for dump truck. From the results shown they provide an essential implication for construction equipment maintenance cost dynamics that the positive influences of past maintenance cost only last for a very short time (1-5 months) and for farther time the influences tend to be negative or nearly zero. This pattern of past maintenance cost sensitivity gives equipment owners for budget planning for maintenance cost that the very recent maintenance cost record gives an important indication for the planning.

For the sensitivities of past fuel consumption, they tend to reflect the properties of equipment type in response to the variations of fuel consumption, which indicates the workload of the equipment. Based on the results for dump truck model, the sensitivities of past fuel consumption exhibit a positive pattern for time t-0 to t-2. This implies that dump truck is a type of equipment that the defects tend to expose relatively quickly after the machine experienced a massive amount of workload in their servicing period. For the models of Division A and B, as the fleet contains a complicated mixture of equipment with a large variety of equipment types, the sensitivities of fuel consumption do not give much implication for equipment maintenance cost dynamics.

4.3.2.2. Comparison between the Overall Effects of Lagged Maintenance Cost and Fuel Consumption

Table 7 compares the aggregated absolute sensitivities of lagged maintenance cost and fuel consumption. The aggregated sensitivity of maintenance cost and fuel consumption is respectively the sum of absolute sensitivities of all lags of maintenance cost and fuel consumption.

Table 7 Aggregated absolute sensitivities of lagged maintenance cost and fuel consumption for three fleet maintenance cost models

	Dump Truck	Division A	Division B
Past maintenance cost	11.01	41.32	22.04
Past fuel consumption	16.67	34.38	11.43

From Table 7, it shows that the results of comparison between aggregated absolute sensitivities of lagged maintenance cost and fuel consumption for individual equipment category fleet and divisional fleet are different. For divisional fleet, the aggregated absolute sensitivity of lagged maintenance cost apparently is higher than that of lagged fuel consumption. But for individual equipment category fleet (dump truck), the result is opposite. This result conforms to the explanation provided in previous section that divisional fleet contains a mixture of different types of equipment which have different deterioration rates. For divisional fleet comprised of different types of equipment, the mixture has equipment are more sensitive to operations in tear and wear than others. For individual category fleet, as the deterioration rate with respect to workload is uniform or very similar for equipment inside the fleet, fuel consumption is a meaningful indicator on equipment overall workload, and on the subsequent equipment maintenance and repair amount and cost. As suggested in previous section, the fuel consumption provides very limited information on equipment cost variations for division fleet maintenance cost modelling. However, even for individual category fleet which has aggregated absolute sensitivity of fuel consumption than that of maintenance cost, the aggregated sensitivity of lagged maintenance cost is still significant which indicates that past maintenance cost is an essential input parameter for modelling of fleet maintenance cost.

4.4. Summary

In this chapter, the construction equipment fleet maintenance cost modelling by GRNN based time series method is presented. The results show that the GRNN based multivariate time series approach provides the most satisfactory prediction performance with the least Mean Absolute Percentage Error (MAPE) in prediction horizon. They also show that the addition of lagged fuel consumptions as input parameters in the model improves the performance for individual category fleet maintenance cost modelling while the same does not apply on divisional fleet maintenance cost model as the divisional fleet contains various types of equipment which have different deterioration rate. The sensitivity analysis conducted by Latin-Hypercube One-Factor-at-a-Time (LH-OAT) method produces the behaviours of sensitivities of lagged maintenance cost and lagged fuel consumption to future maintenance cost and gives some important implications.

5. Construction Equipment Lifecycle Maintenance Cost Modelling

5.1. Introduction

This chapter presents the modelling of construction equipment lifecycle maintenance cost. While fleet maintenance cost modelling provides important information on aggregate maintenance cost of a group of equipment of different age, the modelling of lifecycle maintenance cost studies the maintenance cost dynamics of equipment throughout its service age. Having conducted the modelling and prediction of lifecycle maintenance cost, vital information on determination of optimal equipment replacement timing is obtained. In this part of research, the modelling algorithm adopted is, as suggested as a method with lowest error for prediction in previous chapter, multivariate GRNN based time series method. The results of prediction of lifecycle maintenance cost will be discussed and analysed. To examine the effectiveness of GRNN model of lifecycle maintenance cost in facilitating the optimal replacement decision making, the GRNN model will be fit into a simple optimal replacement model which is developed based on net revenue maximization. Discussion will be provided on the effectiveness of GRNN model of maintenance cost for optimal replacement.

5.2. The Lifecycle Maintenance Cost Model

5.2.1. Data

The data for the modelling of construction equipment lifecycle maintenance cost are from the same Canadian contractor's maintenance database as described in the previous chapter. The database provides the maintenance cost records of each equipment included every month. For each month the raw data contain maintenance cost records of equipment of different ages. To use the data to represent the lifecycle maintenance cost time series, the data is transformed as maintenance cost against age instead of maintenance cost against calendar time and a lifecycle time series is formed by a sequence of maintenance cost with equipment service age as time domain. The same processing applies on the fuel consumption records to form a lifecycle fuel consumption time series. In order to examine the general behaviour of maintenance cost of construction equipment lifecycle, the time series of all equipment units of a category will be averaged and this averaged time series will be used for modelling. In this study, the selected equipment category for analysis is dump truck (10 wheels).

5.2.2. Lifecycle Maintenance Cost Time Series Modelling by GRNN

5.2.2.1. Stationarity test

This study applies Augmented Dickey-Fuller Test (ADF), which is described above, to examine the existence of unit root(s) in the dump truck lifecycle maintenance cost and fuel consumption time series. The lag length used in the ADF test is determined by Akaike's Information Criterion. Table 8 shows the result of t-statistic of the three maintenance cost time series and their respective fuel consumption time series.

Table 8 Unit root test results for Dump truck lifecycle time series

Time Series	ADF	P-value
Dump Truck Maintenance Cost	-1.397692	0.574373
Dump Truck Fuel Consumption	-0.251662	0.588294

Notes: The p-value is computed under the algorithm of MacKinnon (1996) one-sided p-values

The results show that the dump truck lifecycle maintenance cost and fuel consumption time series have at least one unit root at 95% confidence level as all the p-values shown are larger than 0.05. By first differencing to the time series, the result of ADF test of the differenced time series is listed in Table 9.

Table 9 Unit root test results for differenced Dump truck lifecycle time series

Time Series	ADF	P-value
Dump Truck Maintenance Cost	-7.327780	0.000001
Dump Truck Fuel Consumption	-5.502633	0.000001

Notes: The p-value is computed under the algorithm of MacKinnon (1996) one-sided p-values

The results for first differenced time series indicates that all the lifecycle time series for dump truck have one and only one unit root such that first differencing is sufficient to transform the non-stationary time series to stationary.

5.2.2.2. Model Design and Validation

In this study, a multivariate time series model based on General Regression Neural Network will be developed to model the behaviour of construction equipment lifecycle maintenance cost. The input parameters used for the model are lagged maintenance cost and lagged fuel consumption of dump truck. The use of multivariate time series model by GRNN corresponds to results suggested by the previous finding.

In order to determine a suitable lag length for GRNN models, a separate Vector Autoregressive (VAR) modelling is conducted for each with autoregressive order p ranged from 1 to 12 and the Akaike Information Criterion (AIC) of VAR for each p is recorded. The lag length of time series for GRNN models is then determined as the autoregressive order of VAR with the lowest AIC. Table 10 shows the AIC values for different lag length and the result suggests that lag length of 12 is the optimal selection for the time series model.

Table 10 AIC for different lag lengths

Lag Length	AIC
12	20.64689
4	21.10447
1	21.15464
5	21.17642
6	21.34313
2	21.34369
3	21.39524
7	21.44767
8	21.67495
9	21.76719
10	21.86585
11	21.97285

In this maintenance cost modelling, the first 36 months will be used for model training and 37-48 months of equipment lifecycle will be used for validation. For validation set (37-48 months), the predicted value of each pattern will be used as input for next patterns while a separate optimal ARMA developed based on fuel consumption time series in training set and selected by lowest AIC, from $p, q \in (1,2,\cdots,12)$ and $d \in (0,1,2)$ where p, q and d are autoregressive order, moving average order and order of difference respectively, is used to predict the values of fuel consumption for validation set such that the model can predict the maintenance cost dynamics of 12 months completely ex-ante. The optimal ARMA selected for fuel consumption prediction for validation set of maintenance cost model is in form of (2,1,3). To validate the performance and provide proxies to compare the performance of GRNN model on maintenance cost time series in this study, twelve out-of-sample values, representing differenced maintenance cost of 12 months ahead of time, is predicted and integrated to reflect the practical prediction of maintenance cost. The integrated predicted values of maintenance costs will be validated by measuring the Mean Absolute Percentage Error (MAPE) and coefficient of determination (r^2) by comparing the predicted values and the actual values.

5.2.3. Results

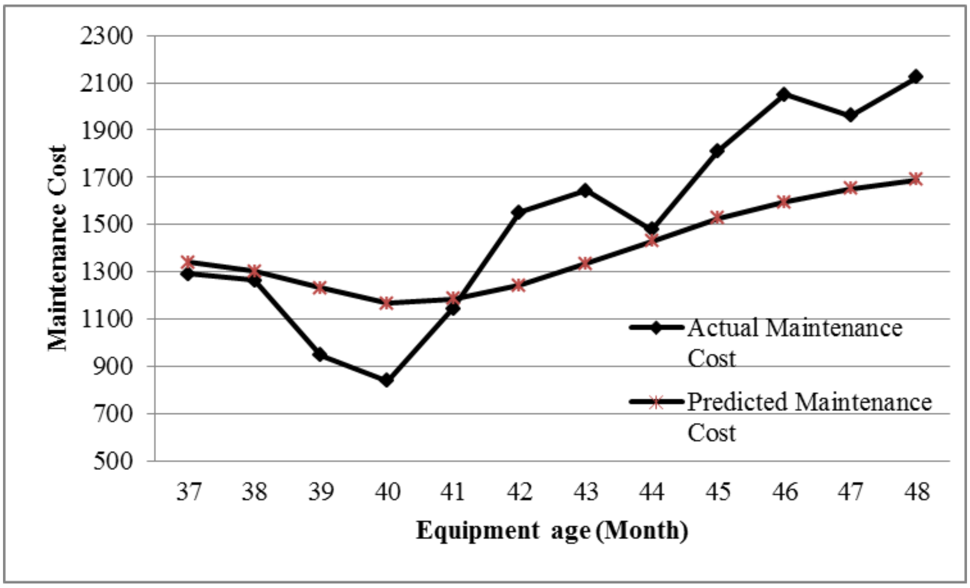

Figure 11 Actual and predicted maintenance cost for out-of-sample prediction horizon

Table 11 MAPE and $\boldsymbol{r^2}$ for GRNN prediction

Equipment Age (Month)	Absolute Percentage Error
37	3.68%
38	2.88%
39	29.90%
40	38.81%
41	3.52%
42	19.94%
43	18.79%
44	3.29%
45	15.73%
46	22.30%
47	15.76%
48	20.50%
MAPE	16.26%
r^2	0.832178

Table 11 and Figure 11 illustrate the performance of prediction by GRNN for equipment maintenance cost. GRNN model provides a r^2 as 0.832178 and MAPE as 16.26% and it suggests that GRNN can adequately model and predict the behaviour of construction equipment maintenance cost time series and provide important information for optimal equipment replacement modelling.

5.3. Optimal Equipment replacement modelling

5.3.1. Overview

This section describes incorporation of GRNN prediction of equipment maintenance cost into a simple and realistic model for optimal equipment replacement decision making and demonstrates the optimal equipment life can be known prior to when it actually happens, based on GRNN prediction with no assumptions on the failure frequency and probability distribution of equipment. The modelling for optimal replacement done by prior studies mainly relies on assumptions on failure rate and maintenance cost dynamics (For example, Matthew and Kennedy (2003), Dreyfus (1960), Love and Guo (1996), Yatsenko and Hritonenko (2010), etc.). These assumptions can cast significant difficulty in real-life application if the assumption of dynamics of maintenance cost does not conform to the reality. The attempt of use of GRNN based time series model in optimal replacement model will be presented with purpose to examine the effectiveness of use of statistical model built by actual data (GRNN model in this study) for optimal replacement decision making without any explicit assumptions on maintenance cost dynamics.

In this study, a simple optimal equipment replacement model which is based on net revenue maximization of equipment is developed based on the ideas of Gransberg et al. (2006) which introduces an optimal replacement policy that maximizes the wealth generated by equipment over its whole life. This model assumes no technological advancement of equipment to examine endogenous dynamics of equipment lifecycle.

5.3.2. The Optimal Replacement Model

The total net revenue, N, for time t is defined by:

$$N_t = N_{t-1} + Y_t - C_t \tag{11}$$

where Y_t and C_t are marginal revenue and marginal cost at time t respectively.

Equation (11) displays an accumulated net revenue of equipment in which the marginal revenue and marginal cost determines the change of wealth for the construction equipment.

Y_t is determined mainly by its return. It can be in form of direct return which is derived from its usage for the owner and also be in form of rental return which the owner rents the equipment out. In this study, the latter is used as the equipment within the database is chiefly for rental. The rental return R is given by:

$$R_t = rS_t \tag{12}$$

Where r is the reference rental rate and S_t is the resale value of equipment at time t. Therefore, Equation (12) can be interpreted as rental return of equipment is a linear function of the resale value and indirectly the depreciation of construction equipment. The reference rental rate is provided by Nova Scotia Road Builders Association (2012) which suggests a monthly rental rate for equipment and produces a monthly rental estimates by multiplying the rental rate and the value of the equipment.

Apart from return of the equipment, capital allowance also forms a part of revenue from equipment (Eilon et al., 1966). For Canada, where is the source of database, the owner is able to receive annual allowance for equipment under reducing balance method. Adjustments may be required for application of this model under different regulatory arrangements.

In sum, Y_t can be defined as:

$$Y_t = R_t + A_t \tag{13}$$

Where A_t is the capital allowance at t.

C_t is mainly divided into cost of ownership and cost of operation[3]. Ownership cost of equipment includes capital cost and loss of resale value of equipment. The capital cost describes the financing cost for equipment investment. In this study, annual interest

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[3] Vorster and Sears (1987) suggested that failure of equipment forms extra cost on whole production process by increasing the cost of the same production as the whole resources allocation for that production may be altered with additional costs. However, in this study, this cost is not included in the model because the equipment in the database is used for rental purpose but not in-house production and their failures will only incur negligible cost of resources allocation for production.

rate is assumed to be 5% and repayment of equipment purchase cost is assumed to be subject to monthly repayment.

The loss of resale value or depreciation is modelled as a decreasing function of age by reducing balance method. The use of reducing balance method has been suggested as a method for modelling of depreciation of equipment as it tends to reduce the value of equipment faster in its younger age which fits the typical depreciation pattern of equipment (Edwards et al., 1998). The loss of resale value of construction equipment is given by:

$$\Delta S_t = dS_{t-1} \tag{14}$$

Where d is depreciation rate. Reference depreciation rate for Canadian equipment is provided by Patry (2007) in which the author offers actual depreciation rate of different kinds of equipment and assets using the data of Capital Expenditure Survey.

Cost of operation includes costs of maintenance, fuel and consumables (Vorster & Sears, 1987). These costs are divided into direct maintenance cost and indirect maintenance cost (Edwards et al., 1998). The former includes all monetary or nominal costs of maintenance. The latter refers to the time cost of maintenance activities for equipment. It includes the return it can otherwise earn if this maintenance does not happen. This indirect maintenance cost, IM_t, can be defined as:

$$IM_t = r_h dt_t S_t \tag{15}$$

Where r_h is the reference hourly rental rate and dt_t is the amount of downtime of equipment at time t. dt_t can be interpreted as average monthly downtime amount of samples in the database. Figure 12 displays time series of average monthly downtime.

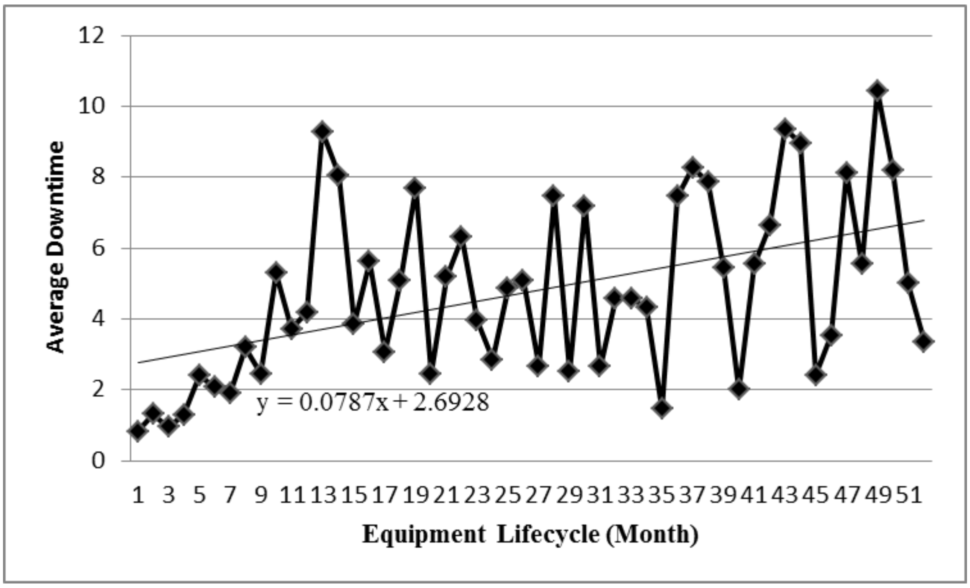

Figure 12 Average monthly downtime along equipment lifecycle

Thus the maintenance cost time series plus the downtime cost represents the marginal operation cost for the equipment lifecycle. The marginal cost of equipment lifecycle can be summarized as:

$$C_t = I_t + \Delta S_t + M_t + IM_t \tag{16}$$

Where I_t and M_t are capital cost and maintenance cost at t respectively.

Substituting Eqs. (8) and (11) into Eq. (6),

$$N_t = N_{t-1} + R_t + A_t - I_t - \Delta S_t - M_t - IM_t \tag{17}$$

And

Maximum N_t is given as:

$$N_{t_o} = N_{t_o-1} + R_{t_o} + A_{t_o} - I_{t_o} - \Delta S_{t_o} - M_{t_o} - IM_{t_o} \tag{18}$$

Where t_o represents optimal equipment replacement time.

By this model, an optimal equipment replacement can be determined with maximum net revenue generated by the equipment. As this model is assumption-free for the part of direct maintenance cost, the results of GRNN model of direct maintenance cost can be directly employed into this model. Using the prediction of M_t by GRNN modeling described in previous section, the incorporation of prediction of M_t into Eq. (18) offers an early prediction of t_o which facilitates an early planning for equipment replacement as equipment transaction is not perfectly liquid. In the following section, the t_o predicted by using the predicted direct maintenance cost by GRNN model will be compared to actual t_o, with other variables can be estimated by the reference data prior to the beginning of service of equipment, to examine the effectiveness of the combination of GRNN modelling into optimal replacement model.

5.3.3. Results

Table 12 illustrates the comparison between optimal equipment life and predicted optimal equipment life. The actual optimal life is 41 months while the predicted value of optimal life based on prediction of maintenance cost by GRNN model is 42 months.

This gives similar values between optimal equipment life and predicted optimal equipment life. It shows that the use of GRNN prediction of direct maintenance cost on optimal equipment replacement decisions provides an early and near-optimal indication on replacement timing. This near-optimal prediction suggests that with aid of GRNN equipment owners are able to plan for equipment replacement in a near-optimal timing 6 months earlier. Figure 13 and Figure 14 display the total and marginal net revenue for out-of-sample prediction period.

Table 12 Comparison between actual optimal equipment life and predicted optimal equipment life

	Length (months)
Optimal equipment life	41
Predicted optimal life	42

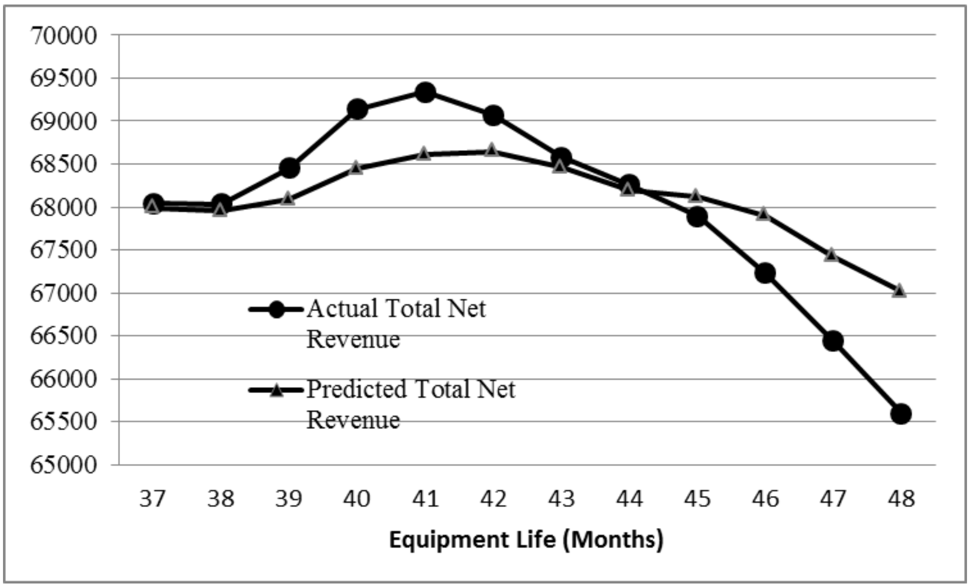

Figure 13 Total net revenue for out-of-sample prediction period

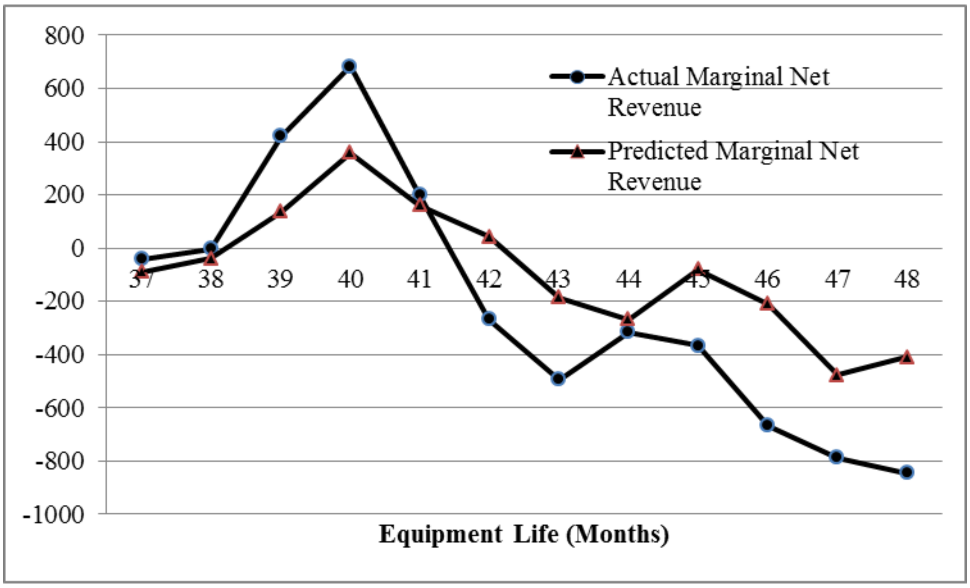

Figure 14 Marginal net revenue for out-of-sample prediction period

This finding demonstrates a successful attempt to incorporate a statistical model of maintenance cost into an optimal replacement model. The results show a couple of advantages of this combination: First, The GRNN model helps to provide a near-optimal prediction of replacement timing of dump truck; Second, this form of optimal replacement model is assumption-free which avoids the potential discrepancy between the actual dynamics and the assumptions if made; Third, the development of GRNN maintenance cost model inside optimal replacement model completely depends on the actual data of maintenance cost records which provides a better representation of dynamics of maintenance cost as the GRNN based time series model provides a good modelling and prediction results.

5.4. Summary

Existing optimal equipment replacement models generally need assumptions on equipment failure rate and probability distribution and so the maintenance cost dynamics of equipment. This kind of assumption can severely limit the applicability of models if these assumptions fail to reflect the reality of equipment failures as the optimal equipment life predicted by this kind of models can be significantly different to the actual optimal life. In this study, a more direct approach is used to handle the equipment maintenance cost for optimal replacement decision making. Instead of assuming how the equipment fails or how the pattern of maintenance cost is, this study adopts General Regression Neural Networks (GRNN) in multivaraite time series modelling and prediction of maintenance cost and makes use of this prediction in a simple optimal replacement model. The results show that the GRNN model is an adequate modelling algorithm for lifecycle maintenance cost with satisafactory prediction performance and the combination of GRNN and optimal replacement model provides a near-optimal prediction for equipment replacement prior to when the optimal timing happens. This suggests that the incorporation of prediction of maintenance cost by GRNN in optimal replacement model is a meaningful algorithm for optimal replacement decision making without risks caused by assumptions if unrealistic.

6. Conclusions

6.1. Summary of Findings

A comprehensive study of construction equipment maintenance cost modelling and analysis is conducted in this research. The general purpose of the research is to model and understand the equipment maintenance cost dynamics so as to provide important information for related stakeholders including equipment owners and equipment rental companies on financial management and resources allocation such as equipment replacement and budget planning. The use of General Regression Neural Network in time series model is the core algorithm adopted in this study for modelling of construction equipment maintenance cost.

The first part of the study, which is on construction equipment fleet maintenance cost modelling, produces several important findings and implications for management of equipment fleet. Recalling that fleet maintenance cost time series is a sequence of the aggregate maintenance cost of a group of different equipment over time, the modelling of this cost serves to give related stakeholders of construction equipment a valuable methodology to predict future values of time series for practical application. To examine the most appropriate form of time series model, the study investigates the modelling performance of traditional univariate model (ARIMA), traditional multivariate model (VAR), univariate GRNN model and multivariate GRNN model. The comparison of prediction accuracy suggests that the GRNN based multivariate time series model outperforms the univariate GRNN model and two traditional time series methods with least prediction error and in turn indicates that this model is an appropriate type of time series model for construction equipment maintenance cost modelling. The results also indicate that addition of fuel consumption improves the performance of modelling of individual equipment category fleet (dump truck fleet) compared to univariate modelling as it helps to represent the workload and in turn model the deterioration rate with respect to workload in the model.

Based on the multivariate GRNN model, Latin-Hypercube One-Factor-at-a-Time Sensitivity Analysis (LH-OAT) is conducted to examine the influence of each input parameter in the model. An important implication of the results of LH-OAT is that the sensitivities of lagged fleet maintenance cost decay very quickly as number of lag increases. The sensitivity of lagged maintenance cost decays to zero quickly by 1-5 months from t-0. This provides vital information for budget planning for maintenance cost of construction equipment fleet as it indicates that significantly positive autocorrelation only comes from the very recent fleet maintenance cost records. Apart from this implication, LH-OAT gives implications on properties of deterioration with respect to workload of certain kind of construction equipment. It reflects that the dump truck is more likely to experience failures quickly after increase of workload, which is represented by fuel consumption, as the sensitivities of lagged fuel consumption for closer lags (t-0 to t-2) are significantly positive. These findings also provide information of fleet management of equipment owners.

The second phase of research is to study the GRNN based multivariate time series model on construction equipment lifecycle maintenance cost and the use of this model for optimal equipment replacement decision making. By rearranging the time domain of maintenance cost records as age instead of actual time, a lifecycle maintenance cost time series can be extracted for the modelling by GRNN. The results suggest that the model satisfactorily predicts the lifecycle maintenance cost with prediction horizon as 12 months.

The GRNN based multivariate time series model for lifecycle maintenance cost is then incorporated into a simple optimal replacement model in which the optimal replacement timing is determined by time when maximum net revenue of the equipment is attained. Comparing the actual optimal replacement timing with the predicted optimal timing by using the predictions of lifecycle maintenance cost, it shows that the incorporation of GRNN model into optimal replacement model provides a near-optimal prediction of replacement timing. This result suggests that this combination for optimal replacement timing prediction gives meaningful practicability and at the same time, as the GRNN model is assumption-free, without any risks of unrealistic assumptions that conventional optimal replacement models may face.

6.2. Limitations

This study faces a limitation of insufficient data of maintenance records of different equipment categories. While the divisional fleet comprises of a variety of equipment categories, a lot of equipment types contain only a few number of equipment which do not sufficiently provide a meaningful sample for modelling of individual category fleet and lifecycle maintenance cost modelling. And for lifecycle maintenance cost modelling, the purchase dates of equipment of categories other than dump truck are generally absent in which the age of equipment cannot be computed for optimal replacement modelling. Nevertheless, the framework used for maintenance cost modelling is shown with evidence that it can adequately model the maintenance cost dynamics in this study and it is expected that the equivalent can be applied to other equipment categories for maintenance cost modelling with satisfactory performance.

6.3. Futures Works

Based on the findings of this research, the use of this framework is recommended to expand to other equipment categories for both individual category fleet and lifecycle maintenance cost modelling so that the research can cover more categories of construction equipment. Also, this framework can be applied on modelling of downtime cost of equipment during maintenance activity, as mentioned in the section of optimal replacement model that downtime cost, as indirect maintenance cost, is a crucial component of optimal replacement determination.

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