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Predicting the maintenance cost of construction equipment: Comparison between general regression neural network and Box–Jenkins time series models

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ABSTRACT

This paper presents a comparative study on the applications of general regression neural network (GRNN) models and conventional Box–Jenkins time series models to predict the maintenance cost of construction equipment. The comparison is based on the generic time series analysis assumption that time-sequenced observations have serial correlations within the time series and cross correlations with the explanatory time series. Both GRNN and Box–Jenkins time series models can describe the behavior and predict the maintenance costs of different equipment categories and fleets with an acceptable level of accuracy. Forecasting with multivariate GRNN models was improved significantly after incorporating parallel fuel consumption data as an explanatory time series. An accurate forecasting of equipment maintenance cost into the future can facilitate decision support tasks such as equipment budget and resource planning, equipment replacement, and determining the internal rate of charge on equipment use.

1. Introduction

Managing the maintenance cost of construction equipment is an important task for contractors in the construction industry, especially for those engaged in heavy construction work with extensive equipment use. Construction equipment provides the functions of earthmoving, lifting, and logistic supplies and is subject to various types of maintenance work, which include preventive maintenance, predictive maintenance, and running repairs, to stay in normal working conditions. Peurifoy etc. emphasized that "the cost of repairs is normally the largest single component of machine cost, the repair cost constitutes 37% of machine cost over its service life" [1], and Vorster [2] pointed out that costs of repair part and labor make up between 15% and 20% percent of the total equipment budget, and is the most difficult to estimate, decisions regarding repair costs affect the hourly rate as well as the economic life of a machine. Maintenance costs can significantly change depending on equipment characteristics, the maintenance strategies of contractors, working conditions, and operator skills, which bring difficulty to estimating equipment ownership and operating cost for management decisions. One crucial yet challenging management activity is predicting the maintenance costs of equipment at various levels of the equipment-owning organization. An accurate prediction of equipment maintenance costs in the planning horizon facilitates budget planning for equipment operations, maintenance resource allocations, equipment repair, overhaul, and replacement decisions. The modeling of equipment maintenance costs can also reveal the dynamic behavior of equipment maintenance costs as well as their factors, on which management decisions can be made to interfere proactively with and predict maintenance cost variations.

Traditionally, equipment owners in the construction industry (i.e., contractors, government organization, and equipment rental companies) predict the maintenance costs of various construction equipment based primarily on past experience, for example, the maintenance cost of a piece of equipment can be estimated from the historical data of similar equipment under similar conditions. Adjustment factors can be applied to the benchmark values to account for the impact from various factors related to equipment (age, heath conditions, maintenance history, etc.), environment (workloads, working conditions, etc.), and organization (equipment management policy, business nature, etc.). However, judgmental forecasting of future maintenance costs based on experience, intuition and personal knowledge is unreliable due to the inherent random nature of equipment failures. With no consensus on the methodology among industrial practitioners, the statistical modeling of the maintenance cost of construction equipment provides a better quantitative approach to predict maintenance costs in the planning horizon.

Previous research in this area, which has commonly employed linear or nonlinear regression by ordinary least squares, has been conducted by Manatakis and Drakatos [3], Edwards et al. [4–6], Edwards and Holt [7], and Gillespie and Hyde [8], among others. Apart from these conventional regression models, the use of the time series approach in this area or in related fields gives further insights into obtaining a good model of the maintenance costs of construction equipment. Moore [9] found that

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the maintenance cost time series has an inherent autocorrelation among observed cost series. Edwards et al. [4] utilized the centered moving average to analyze the time series of the maintenance cost of construction equipment and isolated its trend of changes. Zhao et al. [10] established an autoregressive moving average (ARMA) model, also known as the Box–Jenkins method [11], to model equipment failures based on transformed data. Durango-Cohen [12] adopted the ARMA with exogenous input model (ARMAX) to model the performance behavior of transportation facilities with the application of the Kalman filter. All these attempts have been made to describe and predict the behavior of equipment performance and maintenance cost by using time series forecasting models and results of various degrees of accuracy were obtained.

Although time series analysis has been traditionally conducted using Box–Jenkins models, artificial neural networks (ANN) have also been used for time series modeling and analysis because of its capability to identify the complex underlying nonlinear relationships among time series data. The use of ANN in modeling and in predicting the maintenance cost of construction equipment has been presented in a number of related research work. Edwards et al. [5] used multilayer perceptron (MLP) to predict future values of the maintenance cost of construction plants and found that MLP neural networks have better performance than that of other modeling algorithms such as multiple regression. Hong and Pai [13] modeled and predicted engine reliability by using various forms of models, which include general regression neural networks (GRNNs), support vector machine, and ARMA, and compared their performance in predicting engine reliability metrics.

Following Moore [9], who found that the time series of equipment maintenance cost has autocorrelations among observed data, this study aims to develop and compare time series models for a cost analysis of construction equipment maintenance by using both traditional Box–Jenkins models and GRNN, a machine learning-based forecasting model. The study first presents a univariate modeling of the time series of maintenance cost by using ARMA and GRNN to predict the maintenance cost of construction equipment based on its historical observations. The impact of fuel consumption on the maintenance cost modeling of both traditional vector autoregression (VAR) and GRNN is then investigated to evaluate the performance of forecasting models after the incorporation of this parallel explanatory variable. Finally, the performance of traditional time series models and that of GRNN models is compared, and their advantages and disadvantages are then discussed.

2. Literature review

The maintenance cost of construction equipment includes the following: (1) regular maintenance, which refers to the change of lubricants, coolants, and filters and routine check on equipment conditions; (2) predictive maintenance, where the equipment is maintained or repaired based on need or imminent failure conditions; and (3) corrective maintenance or emergency repairs, where the equipment must be repaired and restored to normal working conditions after an unexpected breakdown during equipment operations, or routine equipment inspections.

An accurate forecasting model on maintenance costs is critical to various decisions on equipment management, such as allocation, repair, replacement, and retirement, because equipment maintenance costs constitute a major fraction of the total life cycle cost of a piece of equipment. Therefore, considerable research has been devoted to the modeling of equipment maintenance costs in the construction, manufacturing, military, and logistics industries.

A number of maintenance cost forecasting models for construction equipment were developed by Edwards et al. [4–7], who used multiple regression techniques to model maintenance costs by incorporating several exogenous inputs, which include machine weight, type of industry, and company attitude toward predictive maintenance. All three variables are important, but operator skill is not significant to be an explanatory factor. In another research by Edwards et al. [4], a combination of time series analysis and cubic equation estimation was used in the model, in which time is an independent variable, to model the cumulative maintenance cost of construction equipment. In yet another research, Edwards et al. [5] studied the performance of models based on neural networks and multiple regression and found that neural networks provide better performance with smaller variance of residuals. The researchers concluded that both types of models can successfully describe and predict maintenance costs, and they suggested the use of neural network models and the provision of information for the assessment of maintenance policy. Edwards and Holt [7] introduced a stochastic model that uses generated random numbers to predict the cost of future maintenance events.

Studies have also been conducted on the life cycle management and operational cost prediction of construction equipment. Gillespie and Hyde [8] conducted statistical regression of the life cycle cost of heavy equipment by using labor cost, the maintenance cost of parts, and fuel cost for equipment operations. The logarithmic model of life cycle cost as a function of fuel cost shows satisfactory goodness of fit, and machine age does not predict the life cycle cost. On the other hand, the fuel cost of equipment operations can achieve a better fit to the cost observation data.

Mathew and Kennedy [14] developed a theoretical framework for optimal equipment replacement to achieve a maximum net benefit from the equipment by assuming that the failure rate is essentially increasing. Manatakis and Drakatos [3] proposed a predictive model of operating cost as a function of operating hours, engine capacity, and machine power of the dump truck. Edwards et al. [15] developed a linear regression model for construction equipment downtime cost by using machine weights as an independent variable.

Moreover, extensive research on the maintenance and life cycle cost of plant and equipment, as well as properties from other industries could also provide several useful insights into the modeling of the maintenance cost of construction equipment. Morcous and Lounis [16] developed a genetic algorithm-based approach to optimize the life cycle maintenance cost of an infrastructure network. Popova et al. [17] presented a multiple regression model for the behavior of the total maintenance cost of a nuclear power plant by using variables such as the number of previous repairs and the level of risk for loss of electrical generation. Li et al. [18] proposed a generalized partial least squares regression model for warship maintenance cost prediction with relatively few samples.

3. Traditional time series analysis

Traditional time series modeling methods mainly rely on linear relationships among successive observations. The Box–Jenkins or ARMA models are expressed in the following form:

$$y_t = C + \left(\phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p}\right) \tag{1}$$

where

y_t	Modeled value
y_{t-i}, y_{t-j}	Historical observed values
ϕ_i	Autoregressive parameters, $i = 1 \sim p$
θ_j	Moving average parameters, $j = 1 \sim q$
ε_t	Error term
C	Constant.

The former part involves previous values of times series, and is known as the autoregressive part. This part examines the lagged relationship between y_t and its earlier historical values. The latter involves error terms, and is known as the moving average part. This part reflects the relationship between y_t and lagged error terms.

Only historical observations of the time series are used as input for prediction in Eq. (1) and it is defined as a univariate time series model. Multivariate time series models can be used with the inclusion of explanatory time series in the model to account for the influence from independent variables, which have a cause–effect relationship with the target variable. For example, VAR is a typical multivariate time series model expressed as:

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

where Y_t is a $k \times 1$ vector with k observations at time t of the k time series, ε_t is the error term, and ϕ_i is the linear autoregressive parameter. In 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.

Statistical tests are required to identify the nature of the time series modeled so that these traditional models can be implemented. Moreover, the transformation of raw time series data may be necessary to make them stationary (i.e., time series data have a constant mean and variance). The conventional test for the existence of unit root (non-stationary nature) in a time series is the augmented Dickey–Fuller test (ADF) [19]. ADF examines the existence of a unit root by estimating a linear model with the first difference value as modeled value as the response variable, and the value of the time series at time t-1 and the previous first difference values as input variables. The hypothesis is then statistically tested, that is, ADF statistics measure the estimated coefficient for value at time t-1 over the standard error. This value is usually a negative number, and the more negative this number becomes, the more likely that the hypothesis of the existence of the unit root is rejected. If the times series is non-stationary, and the k number of differencing is required to make the time series stationary, then k unit root(s) exist, and the order of integration is expressed as $I(k)$.

For the multivariate time series model VAR, the multiple time series in the model need to be tested for co-integration apart from the stationarity of the individual time series. Co-integration of two or more non-stationary time series means the stationary linear combination of these time series. Co-integrating time series have a long-term equilibrium relationship, but the differencing or de-trending of non-stationary time series tends to remove the long-term equilibrium relationship between the time series. In this case, the detection of co-integration should be tested for the time series, and the simple VAR alternative should be used instead. However, if the time series are stationary, co-integration does not need testing because the long-term relationship is not removed. The Johansen procedure [20], one of the most common methods, can be used as a test for co-integration. A comprehensive review of the Johansen procedure was done by Johnes [21]. The Johansen procedure provides two likelihood ratio tests, namely, the trace test and the maximum eigenvalue test. Both tests involve hypothesis testing, which examines the number of co-integrating vectors that indicate the number of co-integrated time series in the model. If a co-integrating relationship is found among the time series in the model, the vector error correction model should be used instead of simple VAR.

Information criteria are commonly used to test iteratively the possible structure of time series models so that the best model with good fit but less complexity is obtained, and to identify the suitable structure of ARMA and VAR models, that is, the autoregressive order of ARMA and VAR and the moving average order of ARMA as model parameters. For example, the Akaike information criterion (AIC) (Akaike [22]), derived from information entropy, measures the accuracy of candidate model forms and, in the meantime, includes a penalty term that increases with the number of parameters included. AIC is given as

$$AIC = 2k - 2\ln(L) \quad (3)$$

where k is the number of parameters and $ln(L)$ is the natural logarithmic value of the maximum likelihood of the candidate model. The maximum likelihood can be approximated, for example, by the following expression (Chatfield [23]):

$$L = N \ln\left(\frac{S}{N}\right) \quad (4)$$

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

4. General regression neural network

4.1. Overview

GRNN is a neural network model proposed by Specht [24] to postulate nonlinear relationships between a target variable and a set of independent explanatory variables. The principle of GRNN is shown in Fig. 1. The target value of the predicted variable is obtained by taking the weighted average of the values of its neighboring points. Close neighbors have higher impact on the target value to be predicted, whereas distant neighbors have little influence. The level of influence (weight) of neighboring points is evaluated by a radial basis function (RBF), such as the Gaussian distribution function, with distance as input and probability value as output: weight = RBF(Distance). The sigma value (standard deviation) of the Gaussian function determines the influence of distant points on the target variable. A larger sigma makes the Gaussian distribution curve more spread (approaching the scenario of taking the average of all point values as the predicted value), whereas a small sigma makes the curve more compact (approaching the scenario of taking the value of the closest neighbor as the predicted value). In a practical use of the GRNN model, an optimum value of the sigma is determined through optimization.

The advantages of the use of GRNN include its accuracy, ability to model from a relatively small data set, and ability to handle outliers. As a data learning algorithm, GRNN is used to explore the relationship among data in a time series, relevant time series, and intervention variables as follows:

$$Y_t = f\begin{pmatrix} Y_{t-1}, Y_{t-2}, \ldots\ldots, Y_{t-n} \\ X_{1(t-1)}, X_{1(t-2)}, \ldots\ldots, X_{1(t-n_1)} \\ X_{2(t-1)}, X_{2(t-2)}, \ldots\ldots, X_{2(t-n_2)} \\ \ldots\ldots \end{pmatrix} \quad (5)$$

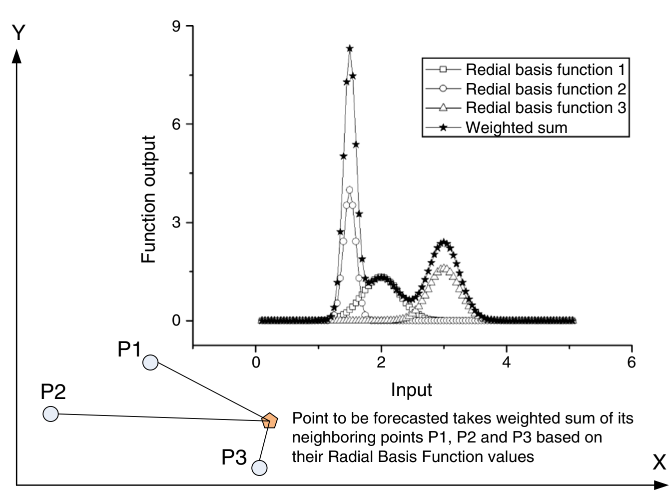

Fig. 1. Weighted sum of redial basis functions for predicting the target variable.

where

Y_t	Current observation
Y_{t-i}	Previous n observations, $i = 1,2,\ldots,n$
X_i	Related time series or invention variable i
$X_{i\ (t-j)}$	Historical observations of explanatory time series or invention variable at (t-j)
n_i	Correlated lagged values of related time series or invention variable i.

Eq. (5) assumes that the current value of observation is related to its previous n observation (autoregression), and the historical observations of related variables (previous n_i observations for variable X_i). The actual nonlinear relationship can be inferred using GRNN. The architecture of GRNN is shown in Fig. 2. The GRNN model has four layers: (1) input layer (each input variable is a neuron in the input layer); (2) pattern layer (after receiving values from the input layer, each neuron in the pattern layer processes the mapping between input vectors and the output of one pattern based on the Euclidian distance from its neighboring points and the smoothing parameters, as shown in Fig. 1); (3) summation layer (takes the sum of weighted target values from each observed case and the sum of weights); and (4) output layer (takes the weighted average of all observed cases). The learning process can be explained below:

(1) The observed time series data (such as fuel consumption) along with related parallel observations (such as eco-operator index and PM event indicator) are represented. Current fuel consumption is related to historical observations and relevant factors. Each input neuron also standardizes the range of values of an input variable by subtracting the median and dividing the difference by the interquartile range.
(2) The optimum sigma value for the training data set is determined using the leave-one-out method, which measures error by building a model with all training rows except for one and then evaluating the error through the excluded row. This procedure is repeated for all rows, and finally, the error is averaged. The optimum sigma value is chosen to minimize model prediction error [25].
(3) The Euclidean distance is used as the distance function from point X to observed point X_i.

$$D_i = \sqrt{(X-X_i)^T(X-X_i)} = \sqrt{\sum_{i=1}^{n}(X-X_i)^2} \tag{6}$$

(4) The weighted sum of all observed points is determined (more weights are assigned if distance D_i is small)

$$s_w = \sum_i^n y_i e^{\left(\frac{-D_i^2}{2\sigma^2}\right)} \tag{7}$$

(5) The sum of weights from all observed n points is determined as

$$s_s = \sum_i^n e^{\left(\frac{-D_i^2}{2\sigma^2}\right)} \tag{8}$$

(6) The predicted value of the target variable can be derived by taking the weighted sum divided by the sum of the weights of n observed points:

$$y = \frac{s_w}{s_s}. \tag{9}$$

5. Problem statement

Maintenance cost forecasting is an important task for contractors in managing an equipment fleet. The accurate prediction of maintenance cost based on historical records provides a basis for budget planning, equipment replacement, tender price estimation, etc. In this study, a road building and maintenance contractor own a large fleet comprised with over 1000 pieces of engineering vehicles and heavy equipment. The contractor estimates the equipment maintenance cost mainly by judgmental forecasting based on historical data at various levels (e.g., organizational, or subordinate, equipment group) with appropriate adjusting factors applied. Modeling the maintenance costs of construction equipment enables the contractor to understand better the

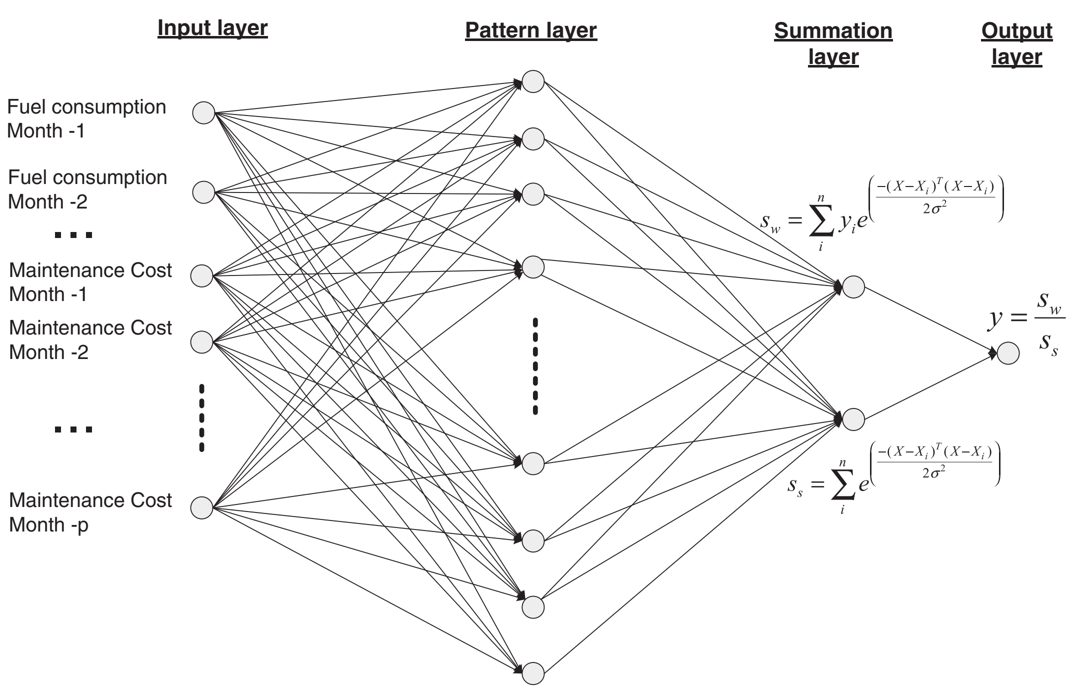

Fig. 2. General regression neural network architecture (-1,-2,..,-p denote the lag number of lagged variables of an observation).

underlying mechanism of cost data variations and to forecast using historical data in the equipment management information system, along with the equipment usage plan. Forecasting is performed for different equipment groups and units at different organizational levels:

(1) Equipment groups: the monthly average maintenance costs of individual equipment groups, such as dump trucks and wheel loaders
(2) Equipment fleet at divisional level: the monthly total maintenance costs of equipment fleet in operational divisions.

Different models are established for cost forecasting on selected equipment groups and operational divisions of the contractor and compared in terms of complexity, interpretability, and forecasting accuracy to identify appropriate models for maintenance cost forecasting in different scenarios.

6. Modeling and analysis of construction equipment maintenance cost

6.1. Data

Data for the maintenance cost of construction equipment modeling are collected from the contractor's maintenance database that is shared across different operational divisions since 1998. The database provides raw data of monthly total maintenance cost for modeling. The total maintenance cost is represented by the sum of preventive maintenance, work order maintenance, and running repair costs, all three of which include their respective labor and repair parts cost. Majority of the total maintenance cost comes from running repair cost, which generally accounts for more than 90% of the sum, whereas preventive maintenance and work order maintenance costs constitute the remaining part. In each maintenance event, parts cost is, on average, about two to three times the labor cost. Apart from the total maintenance cost, the database contains additional information on the fuel consumption of construction equipment. Fig. 3 shows an example of the co-movement behavior of the time series of equipment maintenance cost and of fuel consumption. The time series of maintenance cost of each equipment group and divisional equipment fleet is extracted from the database. In this study, the dump truck and wheel loader (1–2 cubic yards) were selected as equipment categories for analysis, whereas the selected fleets are from two individual operational divisions (Fleets A and B). Therefore, this study compares the maintenance cost behavior of two equipment groups and fleets at two divisions: the former consists of the same class of equipment in a division, whereas the latter constitutes mixed types of equipment in a division. For individual equipment groups, the average maintenance cost per unit, instead of the total maintenance cost of the equipment group, is used to overcome the problem of change in equipment composition with yearly equipment procurement and disposal. The average maintenance cost of equipment in a group is obtained after dividing the monthly total equipment maintenance cost by the number of equipment in service. For divisional equipment fleet, the total maintenance cost is modeled because the total maintenance cost of a large fleet is insensitive to the changes in equipment composition.

6.2. Stationarity test

In traditional time series analysis, time series data are presumed stationary with stable mean and variance. These criteria are particularly important to linear models, such as ARMA and VAR. Thus, for ARMA and VAR model building, diagnosis of the stationarity of the time series is an important step in time series analysis, whereas for GRNN, no differencing is necessary on the time series because the neural network is able to map a non-stationary time series (Kim et al. [26]). This study applies ADF to examine the existence of unit root(s) in the time series of maintenance cost. The lag length used in the ADF test is determined by the AIC. Table 1 shows the results of the *t*-statistic of the four time series of maintenance cost and their corresponding time series of fuel consumption. All time series in this study have no unit roots. As a result, no differencing or de-trending is required to transform the time series.

6.3. Univariate time series modeling

For univariate models for the maintenance cost of construction equipment, ARMA and GRNN are used, and their respective lag orders are determined so that they sufficiently reflect the influence from earlier observations.

For ARMA, both autoregressive and moving average orders 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 12 (one year; i.e.,$0 < p < 12$ and $0 < q < 12$). Each combination of p and q in ARMA is tested against AIC, and the model with a particular

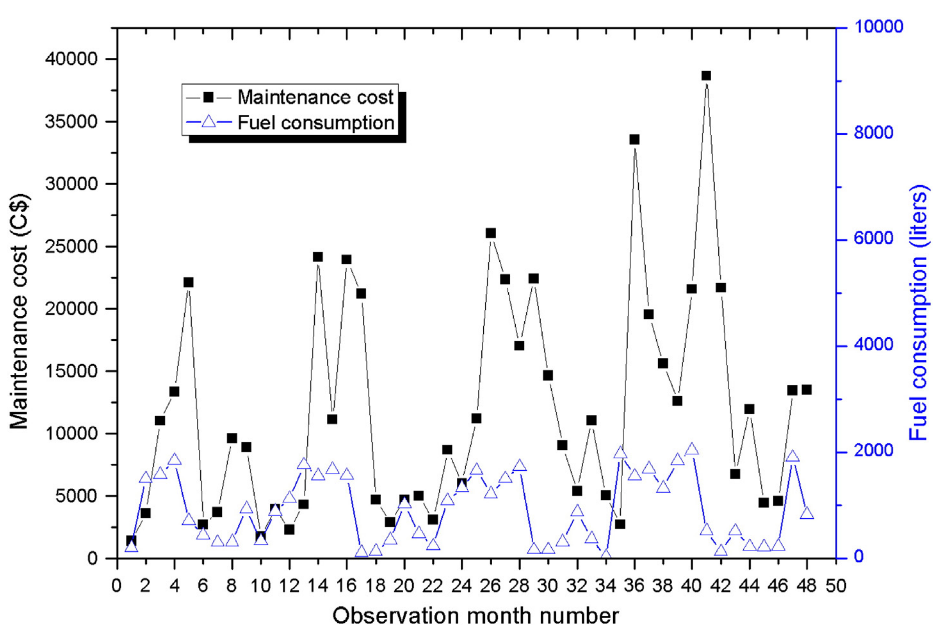

Fig. 3. Co-movement behavior of maintenance cost and fuel consumption of construction equipment.

Table 1
Unit root test results for maintenance and fuel consumption time series after noise reduction.

Group	ADF	p-Value
Dump truck maintenance cost ($)	−0.876	0.331
Wheel loader maintenance cost ($)	−0.539	0.478
Fleet A maintenance cost ($)	−0.032	0.666
Fleet B maintenance cost ($)	−0.213	0.604
Dump truck fuel consumption (liters)	−0.913	0.314
Wheel loader fuel consumption (liters)	−1.164	0.219
Fleet A fuel consumption (liters)	−0.654	0.428
Fleet B fuel consumption (liters)	−0.716	0.401

Notes: The p-value was computed using the algorithm of MacKinnon [27] one-sided p-values.

combination with the smallest AIC value is selected as the most suitable model structure for ARMA for maintenance cost modeling. For GRNN, lag selection follows the autoregressive order based on AIC. Table 2 summarizes the autoregressive and moving average orders for ARMA models and the lag length for GRNN models.

6.4. Multivariate time series modeling with fuel consumption

Apart from the lagged relationship from the given time series, other factors are considered to have significant influence on the future values of the maintenance cost of construction equipment. Gillespie and Hyde [8] observed that fuel expense is crucial to the modeling of the life cycle cost of heavy equipment. However, one drawback of the use of fuel expense as exogenous input is that unit fuel expense, similar to crude oil price, is very likely to fluctuate; thus, fuel expense may not accurately reflect the exact fuel consumption and equipment usage. In this study, fuel consumption, instead of the time series of fuel expense, is employed to facilitate the modeling of the maintenance cost of construction equipment, and GRNN and VAR are used for multivariate time series modeling.

The long-term dynamics of the time series can be maintained because the maintenance cost and the time series of fuel consumption are stationary based on the ADF test. In this case, no co-integration test should be conducted. Therefore, simple VAR can sufficiently model the four pairs of time series.

Similar to the procedure for lag determination in the univariate approach, the autoregressive order of VAR is determined by AIC, with p ranging from 0 to 12. For GRNN, the uniform lag length is determined for both maintenance cost and the time series of fuel consumption similar to VAR. This lag length follows the autoregressive order of VAR. Table 3 summarizes the autoregressive order of the ARMA model and the lag length of the GRNN model.

6.5. Model validation

Chatfield [23] emphasized that different forecasting models and methods should be compared on the basis of genuine out-of-sample predictions. In this research, the observed cost series (N observations) is divided into two parts. The latest m (m = 12) observations are taken as the validation dataset, and all the earlier observations are used for model training. The twelve out-of-sample values, which represent the maintenance cost of 12 months ahead of forecasting time, are reserved for validation tests. Based on the forecasting and actual observed values of the validation dataset, the model is validated by measuring the mean absolute percentage error (MAPE) of the forecasting over the validation dataset. MAPE is defined as:

$$\mathrm{MAPE} = \frac{\sum_{t=N-M+1}^{N} \left| \frac{x_t - x_{t-1}}{x_t} \right|}{M} \tag{10}$$

where

N the number of observations in time series
M the number of validation data
x_t the observed value at time t
x_{t-1} the forecasted value of x_t based on observed time series up to x_{t-1}.

MAPE is taken as the average absolute percentage error measured over the m reserved observations (m = 12 in this study) so that the performance of the different time series models can be evaluated and compared. MAPE measures the forecasting accuracy of models on the maintenance costs of different equipment group or fleets. The forecast model with a lower MAPE value is preferred, which indicates a better model with smaller deviations between the predicted and actual values of the time series.

For univariate ARMA, multivariate VAR, and GRNN, one-step-ahead approach is used for prediction, that is, the predicted value of each out-of-sample prediction result is used as input for the next prediction step.

7. Comparison of ARMA, VAR, and GRNN models

Table 4 summarizes the results of MAPE measured in the prediction periods of the maintenance cost of construction equipment for the four univariate and multivariate models. Figs. 4–7 show the prediction results compared with the actual time series of maintenance cost. Overall, the four models predict the four time series with fair levels of accuracy, with an average MAPE ranging from a maximum of 25.7% for VAR and a minimum of 20.4% for multivariate GRNN. Despite the difference in accuracies, the four time series models can adequately predict the behavior of the time series of construction equipment maintenance cost. The

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

Time series models	ARMA		GRNN
	Autoregression order	Moving average order	Lag length
Dump truck maintenance cost	5	12	5
Wheel loader maintenance cost	7	11	7
Fleet A maintenance cost	5	12	5
Fleet B maintenance cost	8	12	8

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

Time series models	VAR	GRNN
	Autoregression order	Lag length
Dump truck group maintenance cost	3	3
Wheel loader group maintenance cost	7	7
Fleet A maintenance cost	10	10
Fleet B maintenance cost	6	6

Table 4
Prediction performance (MAPE) of the four models for four equipment maintenance cost time series.

Time series models	ARMA	VAR	Univariate GRNN	Multivariate GRNN
Dump truck group cost	27.65%	27.46%	25.43%	16.68%
Wheel loader group cost	19.26%	34.78%	20.85%	18.19%
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	23.05%	25.74%	23.90%	20.36%

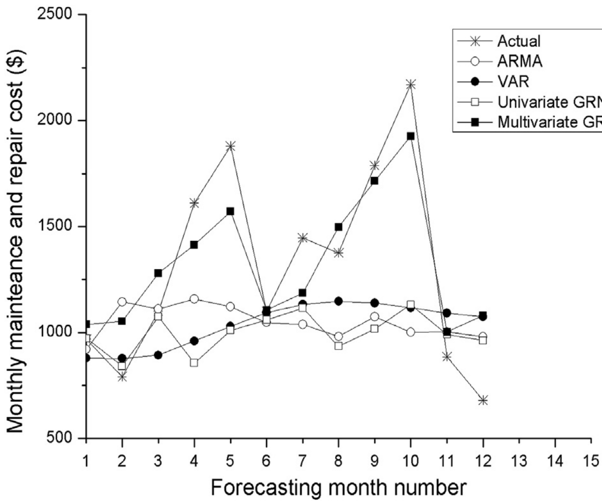

Fig. 4. Prediction performance of different models for the average maintenance and repair cost of a dump truck.

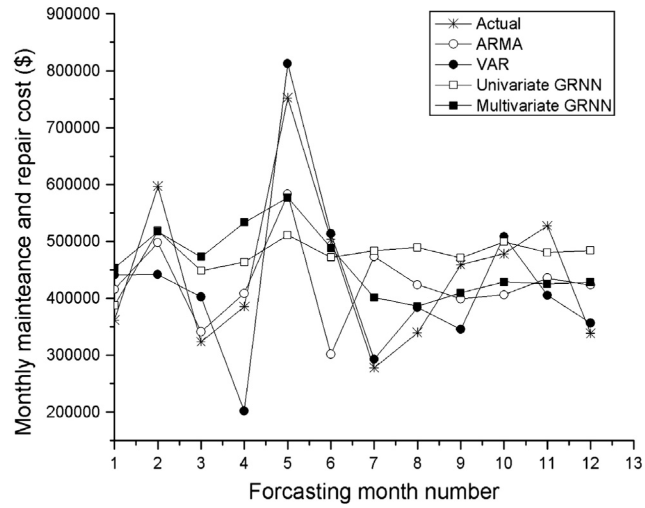

Fig. 6. Prediction performance of different models for the maintenance and repair cost of Fleet A.

use of GRNN with input of both historical maintenance costs and the time series of fuel consumption is the best model for the maintenance cost of construction equipment.

However, the multivariate GRNN only slightly outperforms other models. GRNN is a nonlinear regression surface estimator and an adaptive estimator of the output of a particular input pattern based on its closeness to other patterns. GRNN can be constrained by its iterative learning algorithm. The network might be "trapped" in the local minimum of the error surface and might stop training although the global minimum of error has not yet been reached because of the iteration of searching an optimal smoothing parameter. This phenomenon can affect the modeling capability of GRNN as a regression surface estimator. Given this constraint, although the traditional univariate ARMA does not perform as well as multivariate GRNN, it provides a meaningful alternative modeling of the maintenance cost of construction equipment. Aside from prediction performance, the interpretability of the ARMA model is better than that of neural network models.

Although neural networks are black-box models, the different effects of input parameters in ARMA can be identified, which enhances the analysis of the time series dynamics by studying the influences of the different lags of the time series for equipment management decision-making. Furthermore, traditional ARMA modeling has an established procedure for model parameter identification, which includes the optimal value of autoregressive and moving average order (e.g., by AIC) and testing the stationarity of the time series (e.g., by ADF test). On the other hand, for the use of GRNN in the time series approach, no consensus of method exists in determining the lag length. (In this study, the lag length of GRNN follows the autoregressive order of ARMA for the same time series modeling) These features make ARMA a viable alternative approach to model maintenance cost for construction equipment industry practitioners, considering that the difference in performance between multivariate GRNN and ARMA is not significant.

The traditional time series analysis paradigm and the neural network approach have different performances in univariate and multivariate modeling. For the univariate approach, the performance of ARMA is similar to that of GRNN, whereas for the multivariate approach, GRNN models generally perform better than VAR models. The reason for this phenomenon is that, for the univariate approach, a linear and simpler model is sufficient to describe the serial relationship within a time series. However, for multivariate modeling, a nonlinear learning algorithm such as GRNN is needed to depict the underlying complex relationship.

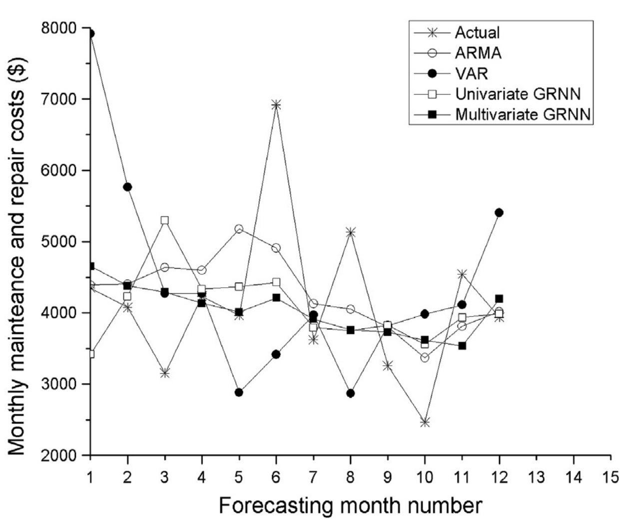

Fig. 5. Prediction performance of different models for the average maintenance and repair cost of a wheel loader.

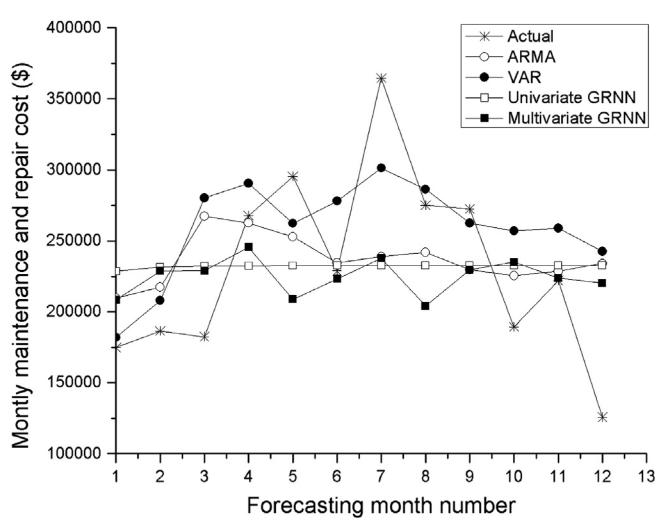

Fig. 7. Prediction performance of different models for the maintenance and repair cost of Fleet B.

8. Effect of fuel consumption on time series modeling

The amount of fuel consumed by construction equipment can be used as an indicator of equipment tear and wear which in turn affects the deterioration rate and maintenance costs of equipment during construction. Fuel consumption is a better indicator than the unit of service of equipment (for examples, the hours worked, or the distance traveled), as it also reflects the intensity of equipment workload. Equipment tends to experience more malfunctioning or failures after extended period of working under full-load conditions, therefore the amount of fuel consumption can be a leading indicator of equipment maintenance costs.

Chatfield [23] concluded that "one favorable condition of applying multivariate time series modeling is suitable explanatory variables have been identified and measured, especially when one or more of them is a leading indicator". The incorporation of the time series of fuel consumption as an explanatory variable in the models is found to be useful in the modeling of the maintenance cost of construction equipment. However, the experimental tests also found that the effect of this additional explanatory variable is only effective for individual equipment groups (i.e., dump trucks, and wheel loaders) but not significant for fleet maintenance cost. Table 5 shows a comparison of the average MAPE on equipment groups of the same type of equipment and equipment fleet of mixed types of equipment. For individual equipment groups, univariate GRNN only has a MAPE score of 23.14%, whereas, for multivariate GRNN, MAPE significantly improves to 17.44%. On the other hand, for prediction at the fleet level, the values of MAPE have only minor differences. Thus, for such a prediction, the incorporation of fuel consumption data in the forecasting model does not significantly improve modeling performance. This is attributed to the fact that different types of equipment have different deterioration rates and levels of fuel consumption with different configurations, equipment weight, and equipment engine model within a similar operation period; as a result, the effect of fuel consumption is averaged out. Therefore, fuel consumption provides very limited information for fleet cost modeling in time series method.

The fuel consumption of construction equipment can be reasonably estimated during the planning period because the amount of fuel consumption is closely related to equipment workload, which is related to the nature and scale of the job site in which the equipment is allocated. Therefore, the fuel consumption of equipment, especially the maintenance cost of individual groups of equipment, can be incorporated into a time series model to account for the amount of work the equipment is expected to carry out.

However, the above rule is not applicable to the classical time series models such as Box–Jenkins models. Chatfield [23] emphasized that although VAR may fit training data better than ARMA, it does not always have a better prediction than ARMA. The multiple time series model may not model the behavior of a time series well because parameter uncertainty increases when more input parameters are incorporated in the model [23]; thus, prediction performance may deteriorate. The multivariate linear approach also has more opportunity to overfit the time series by modeling noise and outliers [23], which may have caused the following results of this study: VAR fails to model adequately the behaviors of both maintenance cost and fuel consumption dynamics, and the nonlinear neural network model is a better alternative toward the multivariate time series approach for the modeling of the maintenance cost of construction equipment.

Table 5
Average MAPE of prediction results on individual equipment group (dump truck and wheel loader) and equipment fleet (Fleet A and Fleet B) maintenance cost.

Model types	ARMA	VAR	Univariate GRNN	Multivariate GRNN
Equipment group	23.46%	31.12%	23.14%	17.44%
Equipment fleet	22.65%	20.37%	24.67%	23.28%

9. Discussions on the forecasting of construction equipment maintenance costs

Construction equipment fleet maintenance cost is the aggregated maintenance cost of mixed types of equipment at a top level, fleet maintenance cost forecasting helps to budget for the spending or plan for business expansion of a corporation, or division. On the contrary, forecasting of maintenance cost for equipment groups is useful for planning of lower level operations, including allocation of repair parts, labor, and financial resources. In theory, the top level forecasting can be broken down to the lower level data in their expected proportions (top–down), and the lower level forecasting can be aggregated to get top level forecasting (bottom–up), but both approaches have practical difficulties in real life applications. In top–down approach, it is difficult to determine the proportions for lower level equipment costs, and in bottom–up approach, many equipment units do not have sufficient or reliable data for forecast modeling. As a result, separate forecasting models shall be built for equipment fleet maintenance cost and equipment group maintenance cost to achieve the best forecasting accuracy for each case.

In addition to the budget planning and operating resource allocation, an accurate forecasting of construction equipment maintenance cost is critical for other equipment management decisions. First, the results can be used for equipment replacement or repair decisions. Early or delayed replacement of heavy construction equipment can have significant financial implications for a contractor; forecasting information can help the contractor to make correct decisions; second, the results can be used for setting accurate rate of charge on equipment use, either internally to the project or externally to the renters. Accurate forecasting information can avoid a low rate of charge leading to operating loss, or a high rate of charge leading to loss of market.

As a major component of equipment ownership and operating cost, equipment maintenance cost is difficult to predict due to the random nature of system failures. Therefore, in most of the current methods for estimating equipment cost, the average maintenance cost ($ per unit of service) is used for decision support purpose instead. The methods include Caterpillar method [28]; Corps of Engineers Method [29]; Peurifoy/Schexnayder method [1], etc., however, Gransberg etc. [30] found these methods give much varied results in hourly unit cost for the same piece of equipment, and one major difference lies in the estimation of equipment maintenance/repair costs.

The forecasting models in this research explored the time series modeling of construction equipment maintenance costs, which give more accurate results through explorative data analysis. The better accuracy of the forecasting results can be explained from the following three perspectives: (1) the general or global trend of maintenance cost change is modeled; (2) the change patterns of maintenance cost, as well as the recent maintenance cost history of equipment is modeled; and (3) the explanatory factors of equipment maintenance cost, such as the fuel consumption, can be used as an leading indicator and be incorporated into the model to further improve the forecasting results for equipment groups.

10. Conclusion

In this study, the time series approach was applied to predict the maintenance cost of construction equipment by using both traditional time series and GRNN models. Time series approaches can utilize the overall trend, fluctuation patterns, recent history of cost changes in the forecasting models; a comparison of traditional linear and nonlinear GRNN models reveals that nonlinear neural network models can better characterize the relationship between the current value of maintenance cost and historical observations of both maintenance cost and related explanatory time series.

Additional information on equipment operations, such as fuel consumption, can improve the forecasting accuracy of the maintenance cost of equipment categories because the amount of fuel consumption can generally reflect the accumulated equipment operational duration and workloads. A change in equipment fuel consumption usually causes a change in equipment maintenance costs with or without lagged effects. The incorporation of this information in the multivariate time series models (both linear and nonlinear) can be used to explain the fluctuation of maintenance cost; thus, forecasting results on the maintenance cost of individual equipment groups are significantly improved. On the other hand, incorporation of equipment fuel consumption into the fleet maintenance forecasting model cannot effectively improve the forecasting results as the equipment fleet is comprised of mixed types of construction equipment, fuel consumption is not always a leading indicator of equipment maintenance cost for all types of equipment, and the data change patterns tend to be smoothed out after aggregation.

Compared with the current methods for estimating equipment maintenance costs, the time series modeling approaches are studied and different types of models are compared in this research, it is concluded that forecasting results can be used for making better equipment management decisions, such as equipment-related resource allocation, equipment replacement, determining the internal rate of charge on equipment. However, time series approaches can only be used to supplement the current practice, both Box–Jenkins models and GRNN models are the best approximations of the maintenance cost time series, most of the model parameters are determined through trial and error based on established scientific method, it is not always possible to explain and validate these models using explicit knowledge. The decision makers should make an independent assessment on the forecasting results based on the current practice and expert opinions. Future research in this area can be extended to cover the topics of sensitivity of model parameters, forecasting of maintenance cost intervals rather than point values, more extensive tests and validation using other types of numerical forecasting models, and so on.

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