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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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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