Rolling stock maintenance strategy selection, spares parts’ estimation, and replacements’ interval calculation

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Abstract

The purpose of this paper is to permit an approach for: (1) selecting a maintenance strategy for rolling stock and (2) obtaining possible spare parts’ quantities and replacement intervals for the components of rolling stock. The methodology adopts an analytic network process (ANP) technique for the strategy evaluation, because ANP considers the important interactions among evaluation factors. The ANP’s result decides upon a proper rolling stock maintenance strategy formed by various combinations of preventive maintenance (PM) and corrective maintenance (CM). The ratio PM/CM, obtained by ANP, can help to predict spare parts’ quantities of the components of rolling stock. The empirical result also indicates that preventive maintenance should be much more valued than corrective maintenance. In addition, safety is considered the most crucial factor for the selection of a rolling stock maintenance strategy. The fruit of this study serves as a reference for railway system operators when evaluating their rolling stock maintenance strategy and also when estimating their spare parts’ quantities and replacement intervals for specific components of the rolling stock.

1. Introduction

The maintenance of rolling stock can be categorized into two types: corrective maintenance and preventive maintenance. The time intervals at which preventive maintenance is scheduled are dependent on both the life distribution of the components and the total cost involved in the maintenance activity, but corrective maintenance cannot be avoided when component failure component occurs. The total cost of maintenance depends on the percentages in performing preventive maintenance and corrective maintenance. In general, more frequent preventative maintenance drives up the total maintenance costs for rolling stock. On the other hand, proper preventative maintenance can potentially reduce the risks associated with rolling stock mechanical failure. Thus, railway system operators are constantly left weighing the safety risks against the maintenance costs. In contrast to maintenance strategy selection in the manufacturing industry, the maintenance of rolling stock also impacts passenger comfort. Because preventative maintenance and corrective maintenance affect these three factors (safety, comfort, and cost), railway system operators must establish a maintenance strategy that strives for an optimum balance. Given this, a method that defines a proper rolling stock maintenance strategy is invaluable to system operators (railway companies), system safety supervisors (governments), and system users (passengers).

The selection of a suitable rolling stock maintenance strategy is complicated. The system operator needs to simultaneously consider non-metric evaluation factors (safety, quality) and metric evaluation factors (maintenance cost, inventory cost, shortage cost) to select an appropriate strategy. In addition, the strategy selection should consider important interactions among evaluation factors. Therefore, this study adopts an expert decision approach – the analytic network process (ANP) technique – which jointly considers non-metric and metric variables all together to determine an appropriate maintenance strategy. In addition, spare parts’ quantities and replacements’ interval estimation are conducted using the Weibull distribution based on the preventative maintenance (PM)/corrective maintenance (CM) ratio obtained by expert decisions in the ANP analytical result. The results of this study serve as a reference for railway system operators when evaluating their rolling stock maintenance strategy and also when estimating their spare parts’ quantities and replacement intervals for specific components of the rolling stock.

2. Literature review

Many studies on manufacturing system maintenance and replacement problems exist (Mccall, 1963; Barlow and Proshan, 1975; Pierskalla and Voelker, 1976; Sherif and Smith, 1981;
Jardine and Buzacott, 1985; Valedz-Flores and Feldman, 1989; Cho and Parlar, 1991; Ruhul and Amanul, 2000; Yun and Ferreira, 2003; Berthaut et al., in press; Muchiri et al., in press; Sun and Li, 2010), as well as thousands of maintenance and replacement models have been proposed. Most previous research studies on maintenance models have centered around total cost (Ruhul and Amanul, 2000; Yun and Ferreira, 2003). In comparison with manufacturing system maintenance, studies on rolling stock maintenance are relatively rare. Chaudhuri and Suressh (1995) developed an algorithm for determining the best type of maintenance, period length, and replacement policy using fuzzy set theory, but did not consider safety, which could be crucial for rolling stock maintenance. Wang et al. (2007) evaluated different maintenance strategies based on a fuzzy analytical hierarchy process, however, the AHP’s evaluation did not reflect on the possible interaction among the evaluation factors.

In consideration of spare parts, Chelbi and Ait-Kadi (2001) proposed a jointly optimal periodic replacement and spare parts provisioning strategy. They evaluated the performance of this strategy in terms of total average cost per time unit over an infinite horizon. Yun and Ferreira (2003) described the development of a simulation model to assess the inventory requirements of alternative rail sleeper replacement strategies. Almeida (2001) presented multi-criteria decision models for two maintenance problems: repair contract selection and spare provisioning. In the repair contract problem the model incorporates consequences modeled through a multi-attribute utility function. The consequences consist of contract cost and system performance, represented by the system interruption time. Two criteria (risk and cost) are combined through a multi-attribute utility function in the spare provisioning decision model.

As for the replacement interval, Chaudhuri and Suressh (1995), Cassady et al. (1998), and Nakagawa (1989) conducted research on the principles of maintenance cost minimization to determine the best replacement cycle. They considered maintenance costs resulting from preventative maintenance and system damage. Huang et al. (1995) and Ruhul and Amanul (2000) suggested that system damage rates increase with amortization. When damage maintenance costs exceed preventative maintenance costs, a suitable preventative maintenance period will minimize total maintenance costs. This study follows related literature that assumes the Weibull distribution be applied to rolling stock component amortization to obtain a more reasonable result.

Most research studies regarding maintenance strategies and replacement policies have developed models focusing on cost consideration. However, it should be better to consider factors such as safety when developing a model to assist in selecting a maintenance strategy (Wang et al., 2007). Therefore, this study incorporates relevant safety factors by adapting the ANP method which allows for the consideration of important interactions among the evaluation to select an appropriate rolling stock maintenance strategy.

3. Research design and methodology

This study applies expert decision methodology to select an appropriate maintenance strategy from various possible strategies of different PM and CM ratios. Following this selection, the estimation of spare parts’ quantities is established using a multi-criteria decision model based on the ratio of preventative and corrective maintenance obtained previously in the ANP result. In addition, the rolling stock component replacement interval is estimated using the Weibull distribution assumption for the lifetime of the component. The objective of this study is to address a group of identical units of rolling stock.

Experts were surveyed through the use of questionnaires in two phases. Phase 1 interviewed the maintenance staff on site to establish the ANP questionnaire decision hierarchy framework for phase 2. Phase 2 interviewed maintenance managers to obtain an appropriate rolling stock maintenance strategy for deciding upon the preventative and corrective maintenance ratio and also the weight for the evaluation factors. In addition, the multi-attribute utility theory is adopted to estimate the possible spare parts’ quantities in the various planning horizons. Finally, the Weibull distribution is applied to determine the life of components in order to obtain optimal replacement intervals. Fig. 1 presents the analytical procedure.

In this study the maintenance strategy must consider the interaction between selected factors. For example, safety and cost are the two essentials factors affecting a rolling stock strategy selection; however, one must be sacrificed to some degree in favor of the other. The major drawback of the analytic hierarchy process (AHP) lies in the assumption that independent conditions exist. This is sometimes an unrealistic premise, and thus ANP is a more appropriate technique for rolling stock maintenance selection.

3.1. The analytic network process

The analytic network process (ANP) is a multi-criteria theory of measurement used to derive relative priority scales of absolute numbers from expert judgments, which also belong to a fundamental scale of absolute numbers. These judgments represent the relative influence of one of the two elements over the other in a pair-wise comparison process on a third element in the system, with respect to an underlying control criterion. Through a supermatrix, whose entries are themselves matrices of column

---

**Fig. 1.** Research analysis procedure.
priorities, the ANP synthesizes the outcome of dependence and feedback within and between clusters of elements (Saaty, 2004). The ANP is the general form of the analytic hierarchy process (AHP) (Saaty, 1980), but the drawback of it lies in certain limitations when the complexity of decision problems increases and interactions among decision criteria and sub-criteria are not implicitly covered. The ANP is proposed (Saaty, 1996) to overcome the problem of interdependence and feedback between the criteria or alternatives. The ANP methodology has also been applied in areas including priority ranking, substitution production, project selection, optimal scheduling, production planning, performance evaluation, strategic decision forecasts, and risk evaluation (Meade and Presley, 2002; Presley et al., 2007; Liberatore, 1987; Lee and Soung, 2000; Meade and Sarkis, 1999; Sarkis and Talluri, 2002; Sarkis and Sundarraj, 2002; Sarkis (2003a, 2003b); Sarkis et al., 2007; Karsak et al., 2002; Momoh and Zhu, 2003).

The important phases of the ANP compare criteria in the whole system to form the supermatrix. This is executed through pair-wise comparisons by asking “how much importance does an evaluation factor have compared to another evaluation factor with respect to our research goal?” The relative importance value can be determined using a scale of 1–9, representing equal importance to extreme importance (Saaty, 1980, 1996). The general form of the supermatrix can be described as follows:

\[
W = \begin{bmatrix}
C_1 & C_2 & \ldots & C_n \\
e_1 & e_2 & \ldots & e_n \\
\vdots & \vdots & \ddots & \vdots \\
e_{m1} & e_{m2} & \ldots & e_{mn}
\end{bmatrix}
\]

where \(C_m\) denotes the \(m\)th cluster, \(e_{mn}\) denotes the \(n\)th element in the \(m\)th cluster, and \(W_{ij}\) is the principal eigenvector of the influence of the elements compared in the \(j\)th cluster to the \(i\)th cluster. In addition, if the \(j\)th cluster has no influence upon the \(i\)th cluster, then \(W_{ij} = 0\). Therefore, the form of the supermatrix depends much on the variety of the structure. A pair-wise comparison has two goals: one for weighting the clusters (i.e., criteria) and the other for estimating the direction and importance of influence between elements, which are numerically pictured as ratio scales in a so-called supermatrix.

The essential step to apply the ANP approach is to construct the hierarchical decision network. The ANP model needs the definition of elements and their assignment to clusters, as well as a definition of their relationships (Wolfslehner et al., 2005). After determining all the elements that affect the decision, we group them into clusters for each network. Comparisons of clusters, comparisons of elements, and comparisons for alternatives are performed to calculate the relative importance and to construct the unweighted supermatrix. In the supermatrix, each row and respective column represents an element of the decision network. The first row and column represent the “goal” elements. The second middle levels of elements represent the clusters. The next levels of rows and columns represent the components of the clusters. The bottom rows and columns represent the alternatives. For supermatrix formation, the pair-wise comparisons are conducted for the purpose of weighting the clusters and estimating the direction and importance of influence between elements to form a supermatrix. The supermatrix allows a resolution of the effects of interdependency that exists between the elements of the system.

An ANP model is mathematically implemented following a three-step supermatrix calculation (Saaty, 2001). In the first step, the unweighted supermatrix is created directly from all local priorities derived from pair-wise comparisons among elements influencing each other. The elements within each cluster are compared with respect to influencing elements outside the cluster. This also yields an eigenvector of influence for all clusters on each cluster. The second step calculates the weighted supermatrix by multiplying the values of the unweighted supermatrix with their affiliated cluster weights. By normalizing the weighted supermatrix, it is made column stochastic. In the final step, the limit supermatrix is processed by raising the entire supermatrix to powers until convergence (Wolfslehner et al., 2005).

### 3.2. The estimation model for spare parts’ quantity

This study formulates the estimation model for spare parts’ quantity by following Almeida (2001) with some modification. A multi-criteria decision model, \(U(x, z)\), allows the quantification of spare parts by provisioning for a single item and taking into account the total spare cost (\(C\)) and the risk of an item’s non-supply (\(z\)). The assumption to formulate the estimation model of spare parts’ quantities is close to the model formulation of Almeida (2001). The multi-attribute utility function is assumed to be additive as indicated in Keeney and Raiffa (1976), Almeida and Bohoris (1995), and Almeida and Souza (1993). The meaning of the multi-attribute utility function is derived from two main components. The first utility component is derived from minimizing the maintenance cost (mainly from preventative maintenance). The second utility component is derived from minimizing the probability of the shortage of stock of spare parts (much sensitive to corrective maintenance). The basis of this assumption implies an independence condition in preferences between PM and CM (Keeney and Raiffa, 1976). The interaction among PM and CM is considered by the ANP technique in the previous stage.

\[
\max_\alpha U(x, z)
\]

Here, \(U\) means utility, item reliability is assumed to follow a Weibull distribution with given \(\theta\) and \(\beta\), \(\theta\) represents the scale parameter, and \(\beta\) represents the shape parameter. Total spare cost \(C\) depends on the unit cost \(C_e\) and the number of spare parts \(q\):

\[
C = qC_e
\]

The lifetime distribution of spare parts and the investigated single unit are both assumed to follow the Weibull distribution. \(\alpha\) is derived from the probability when the investigated single unit fails and the spare part also fails simultaneously. Thus, we assume \(z = x + y\), where \(x\) means the event indicating the investigated single unit fails, \(y\) means the event indicating the spare part fails, and the occurrences of these two events are independent. The convolution is used to calculate the integration of these two cumulative distribution functions \(F_x\) and \(F_y\), so as to obtain the probability of the provisioning shortage \(\alpha\). When the single unit fails and the spare part also fails simultaneously, the provisioning shortage occurs, and thus:

\[
\alpha = F_{x+y}(a) = P[X+Y \leq a] = \int_{0}^{a} \int_{0}^{a-x} f(x)g(y) dx dy
\]

\[
= \int_{-\infty}^{\infty} \int_{-\infty}^{a-x} f(x)g(y) dy dx = \int_{-\infty}^{\infty} \left( \int_{-\infty}^{a-x} f(x) dx \right) g(y) dy
\]
As before, one-dimension utility functions are first obtained for $U(C(q))$ and $U(Z(q))$, and then a multi-attribute utility function $U(C(q),Z(q))$ is obtained. This multi-attribute utility function is assumed to be additive:

$$U(C,x) = K_1 U_p(C) + K_2 U_r(x)$$

Here $K_1$ is the conditional probability of preventive maintenance and $K_2$ the conditional probability of corrective maintenance; $K_1+K_2=1$, where $K_1$ and $K_2$ value are derived from the ANP result.

Substituting (2) and (3) into (4):

$$U(C,x) = K_1 U_p(qC_1) + K_2 U_r(x)$$

If (5) is applied to (1), then the optimum solution can be obtained while the utility is maximized.

3.3. Component replacement interval estimation

3.3.1. Weibull distribution

A Weibull distribution is very useful as a failure model in analyzing the reliability of different types of systems (Qiao and Tsokos, 1995). Therefore, this study implements it for representing the time to failure of rolling stock components. The Weibull distribution consists of 2 parameters, where $\theta$ represents the scale parameter and $\beta$ represents the shape parameter. The failure time follows the Weibull distribution with a distribution function:

$$F(x) = 1 - \exp \left[ -\left( \frac{x}{\theta} \right)^\beta \right]$$

where $x \geq 0$, $\theta > 0$, and $\beta > 0$.

The probability density function is as follows:

$$f(x) = \frac{\beta}{\theta} \left( \frac{x}{\theta} \right)^{\beta-1} \exp \left[ -\left( \frac{x}{\theta} \right)^\beta \right]$$

where $x \geq 0$, $\theta > 0$, and $\beta > 0$.

The 3-parameter distribution cumulative density function is

$$F(x) = 1 - \exp \left[ -\left( \frac{x-\gamma}{\theta} \right)^\beta \right]$$

where $x \geq \gamma$, $\theta > 0$, $\beta > 0$, and $\gamma \geq 0$.

The difference between the 3-parameter and 2-parameter Weibull distributions is a location parameter represented by $\gamma$. The Weibull distribution is primarily dependent on the scale and shape parameters.

3.3.2. Weibull probability density function parameter estimation

Graphical methods are commonly used for reliability data analyses due to their simplicity and visibility (Jiang and Kececioglu, 1992). The Weibull probability method is a relatively easy and frequently applied graphical approach. It can express the analyses due to their simplicity and visibility (Jiang and Kececioglu, 1992). The Weibull probability method is a relatively easy and frequently applied graphical approach. It can express the exponentiated Weibull distribution as a linear function. The slope is the shape parameter of the Weibull distribution.

Applying a natural logarithm in this equation gives the following:

$$\ln(1-F(x)) = -\left( \frac{x}{\theta} \right)^\beta, \quad -\ln(1-F(x)) = \left( \frac{x}{\theta} \right)^\beta$$

Applying a natural logarithm again gives:

$$\ln[-\ln(1-F(x))] = \beta \ln\left( \frac{x}{\theta} \right) = \beta \ln x - \beta \ln \theta$$

We make $Y = \ln [-\ln(1-F(x))]$, where $X = \ln x$

Rewriting the above function into a straight function, we have:

$$Y = \beta X - \beta \ln \theta$$

Fothergill (1990) used both an exact technique and Monte-Carlo simulations to estimate the cumulative probability of failure. We take $P_i$ as the estimation value for $F(x)$:

$$P_i = \frac{i-0.3}{n+0.4}$$

where $P_i$ represents the $i$th observed cumulative frequency value of $n$ numbers of samples. Therefore, this study applies $F(x)$ for the value estimation followed by a frequency graphic analysis expressed as $Y = \ln [-\ln(1-F(x))]$, and $X = \ln x$ to obtain the scale (characteristic life) and shape parameters of the Weibull distributions $\theta$ and $\beta$. This study follows Huang et al.'s (1995) mathematical model $T_0 = 0.1 \times T_i \times \theta$ to find the optimal replacement interval $T_0$, where $T_i$ is the average service time of a component under the PM policy (MTBF, mean time between replacement). The $\theta$ value is obtained from sampling the replacement data. Replacement time $T_i$ is achieved through the $\beta$ value and the ratio between corrective and preventive maintenance costs.

4. Empirical result analysis

4.1. Selecting an appropriate maintenance strategy

This study applies the ANP technique expert questionnaire survey to select an appropriate rolling maintenance strategy. Accordingly, this study finds evaluation factors affecting the maintenance strategy selection via a literature review and experts’ opinions. These evaluation factors and higher-level evaluation factors derived from factor analysis shape the evaluation framework of the ANP questionnaire. Finally, there are three different maintenance strategies based on various combinations between PM and CM.

Alternative A: the frequency ratio between PM and CM is 7:3.
Alternative B: the frequency ratio between PM and CM is 1:1.
Alternative C: the frequency ratio between PM and CM is 3:7.

This study uses the model 321 metro rolling stock current collecting shoe as a component for analysis according to rolling stock maintenance experts' suggestion. In addition, the 321 metro rolling stock collecting shoe is crucial for the daily operation of Taipei's mass rapid transit (MRT). The ratio of PM:CM = 7:3 is derived from the sample component data for analysis. Of the 50 components randomly sampled, 35 samples executed preventive maintenance and 15 executed corrective maintenance. Therefore, we derive the ratio of PM:CM (= 7:3) for our first possible maintenance strategy alternative. Because the aim of this study is to investigate the importance between preventive and corrective maintenance in the rolling stock maintenance strategy selection, the second possible maintenance strategy alternative PM:CM = 1:1 is then created, indicating that preventive maintenance had the same importance as corrective maintenance in the rolling stock maintenance strategy selection. The third alternative is created by the ratio of PM:CM (= 3:7), which means preventive maintenance is less important than corrective maintenance. The ratio PM:CM multiplied by the weight obtained by the ANP analysis can help predict the preparation for spare parts' quantities of the rolling stock component by maximizing the multi-attribute utility.
4.2. Questionnaire design and investigation

This study adopts a two-phase questionnaire design. The first phase of the questionnaire is designed by following Shu (1999), who considered some specific factors affecting maintenance strategy selection. Interviews are conducted on site with the maintenance staffs who work for various railway system operators, including conventional railway system, mass rapid transit systems, and high-speed rail system. A total of 78 questionnaires were returned. This study applies the factor analysis technique to conduct data reduction and summarization, and then extracts high-level evaluation factors to form the decision hierarchy of the ANP questionnaire. The ANP technique could aid in selecting the most suitable rolling stock maintenance strategy based on experts’ choice. Table 1 presents the first phase questionnaire distribution information.

4.2.1. Factor analysis results

This study adopts the KMO test and Bartlett test to examine the appropriateness of 13 factors on rolling stock maintenance for factor analysis application. The result shows a KMO value greater than 0.7 and a Bartlett test value at 635.797, indicating the appropriateness of factor analysis application in rolling stock maintenance-related issues. Rolling stock maintenance factor analysis results show evidence of total explainable variance at 71.143% and extract three high-level factors. As for the reliability analysis result, this study conducts a Cronbach’s α value to examine the rolling stock maintenance questionnaire reliability to assure all measured factors are highly consistent. Table 2 presents the factor analysis result and shows that all Cronbach’s α individual are above 0.7.

4.2.2. ANP questionnaire design and empirical result

It is suggested that a reduction of the sub-factors be considered when applying the ANP technique. Therefore, this study groups highly correlated sub-factors into one factor through correlation analysis. Empirical results show a correlation between “reduce rolling stock shut-down time” and “reduce maintenance time” as 0.626. Therefore, we group these two sub-factors together, naming the new group “reduce maintenance cost and shut-down time”. The correlation between “assure worker and staff safety” and “assure passenger safety” is 0.643. Therefore, we group these two sub-factors together, naming the new factor “assure worker and passenger safety”. The correlation of “reduce maintenance cost”, “improve staff work efficiency”, and “improve staff work assignment and preparation” reached as high as 0.780. Therefore, we group these three sub-factors into one sub-factor and call it “improve staff work efficiency”. The correlation between “reduce the impact in case of emergency” and “improve railway system coach failure” reached 0.704. Hence, we group these two sub-factors together and rename it “improve rolling stock failure rate”.

The second phase questionnaire design is based on the factor analysis result of the first phase questionnaire. The second phase questionnaire is based on three main evaluation factors with eight sub-factors and three selection alternatives. This study refers to Taipei’s mass rapid transit system on preventative and corrective maintenance percentages for possible selection alternatives.

The following presents eight reorganized sub-factors categorized into three main factors.

(1) **Factor 1: Quality and Efficiency**
This factor combines four sub-factors: maintain high quality maintenance, improve staff work efficiency, maintain appropriate usable spare parts, and reduce stock failure rate.

(2) **Factor 2: Cost and reliability**
This factor includes two sub-factors: maintain rolling stock in good condition and reduce maintenance cost and shut-down time.

(3) **Factor 3: Safety**
This factor encompasses two sub-factors: assure worker and passenger safety and assure railway rolling stock safety.

<table>
<thead>
<tr>
<th>Interviewee</th>
<th>Distributed questionnaires</th>
<th>Returned questionnaires</th>
<th>Effective questionnaires</th>
<th>Ineffective questionnaires</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional railway maintenance staff</td>
<td>100</td>
<td>40</td>
<td>39</td>
<td>1</td>
</tr>
<tr>
<td>Taipei rapid mass transit maintenance staff</td>
<td>100</td>
<td>29</td>
<td>28</td>
<td>1</td>
</tr>
<tr>
<td>High-speed rail maintenance staff</td>
<td>100</td>
<td>11</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>300</td>
<td>80</td>
<td>78</td>
<td>2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Factor and efficiency</th>
<th>Sub-factor</th>
<th>Factor loading</th>
<th>Eigenvalue</th>
<th>% of variance</th>
<th>Cumulative variance (%)</th>
<th>Cronbach’s α</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality and efficiency</td>
<td>Maintain high quality maintenance</td>
<td>0.615</td>
<td>6.357</td>
<td>48.898</td>
<td>48.898</td>
<td>0.889</td>
</tr>
<tr>
<td></td>
<td>Maintain appropriate available spare parts</td>
<td>0.735</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Improve staff work efficiency</td>
<td>0.643</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Improve staff work assignment and preparation</td>
<td>0.668</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reduce the impact in case of an emergency</td>
<td>0.696</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Improve railway system coach failure rate</td>
<td>0.814</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost and reliability</td>
<td>Maintain rolling stock in good condition</td>
<td>0.436</td>
<td>1.814</td>
<td>13.957</td>
<td>62.855</td>
<td>0.820</td>
</tr>
<tr>
<td></td>
<td>Reduce rolling stock shut-down time</td>
<td>0.812</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reduce maintenance time</td>
<td>0.894</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reduce maintenance cost</td>
<td>0.721</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Safety</td>
<td>Assure staff and personnel safety</td>
<td>0.874</td>
<td>1.077</td>
<td>8.288</td>
<td>71.143</td>
<td>0.810</td>
</tr>
<tr>
<td></td>
<td>Assure railway system safety</td>
<td>0.832</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Assure passenger safety</td>
<td>0.693</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3 indicates the final factors and sub-factors affecting the rolling stock maintenance included in the ANP model. The second phase questionnaires were distributed to middle-high level maintenance executives of Taipei’s mass rapid transit. Qualified interviewees needed to have more than 10 years of rolling stock maintenance experience.

In the ANP application the consistency of the judgments is verified against misevaluations. If a matrix includes inconsistencies, then the respondents are required to review their corresponding evaluations until a reliable judgment is obtained. For an $n 	imes n$ pair-wise comparison matrix, the consistency index is defined as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

Table 3 Evaluation factors and possible alternatives as the basis for the ANP method questionnaire.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Sub-factor</th>
<th>Alternative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality and efficiency</td>
<td>Maintain high quality maintenance</td>
<td>Alternative A: the frequency ratio between PM and CM is 7:3</td>
</tr>
<tr>
<td></td>
<td>Improve staff work efficiency</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Maintain appropriate usable spare parts</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reduce rolling stock failure rate</td>
<td></td>
</tr>
<tr>
<td>Cost and reliability</td>
<td>Maintain rolling stock in good condition</td>
<td>Alternative B: the frequency ratio between PM and CM is 1:1</td>
</tr>
<tr>
<td></td>
<td>Reduce maintenance cost and shut-down time</td>
<td></td>
</tr>
<tr>
<td>Safety</td>
<td>Assure worker and passenger safety</td>
<td>Alternative C: the frequency ratio between PM and CM is 3:7</td>
</tr>
<tr>
<td></td>
<td>Assure rolling stock safety</td>
<td></td>
</tr>
</tbody>
</table>

Table 4 Maintenance strategy expectation index.

<table>
<thead>
<tr>
<th>Cj Evaluation factors Weight ($R_j$)</th>
<th>Maintenance strategy weights</th>
<th>$S_{Cj}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$W_{C1}$</td>
<td>$W_{C2}$</td>
</tr>
<tr>
<td>C1 0.176</td>
<td>0.619</td>
<td>0.244</td>
</tr>
<tr>
<td>C2 0.092</td>
<td>0.521</td>
<td>0.281</td>
</tr>
<tr>
<td>C3 0.294</td>
<td>0.615</td>
<td>0.239</td>
</tr>
<tr>
<td>C4 0.234</td>
<td>0.641</td>
<td>0.230</td>
</tr>
<tr>
<td>C5 0.052</td>
<td>0.615</td>
<td>0.227</td>
</tr>
<tr>
<td>C6 0.048</td>
<td>0.508</td>
<td>0.293</td>
</tr>
<tr>
<td>C7 0.042</td>
<td>0.576</td>
<td>0.268</td>
</tr>
<tr>
<td>C8 0.062</td>
<td>0.629</td>
<td>0.219</td>
</tr>
</tbody>
</table>

Maintenance strategy expectation index $DI_i$ = 0.607 0.244 0.149.

where $\lambda_{\max}$ is the largest or principal eigenvalue of $n \times n$ pair-wise comparison matrix. In this empirical result the consistency index (CI) values are all less than 0.1. Therefore, the result of the expert judgments for the ANP questionnaire can be accepted.

For the evaluation results, Fig. 2 shows cost and reliability, safety, and quality and efficiency, with weight values of 0.268, 0.528, and 0.204, respectively. This result fully explains safety as a first priority in railway rolling stock maintenance considerations. Fig. 2 further shows that maintenance strategy A (0.607) is significantly superior compared to the other two maintenance strategies after the calculation of the maintenance strategy expectation index in Table 4. Therefore, maintenance strategy A’s preventative maintenance and corrective maintenance with percentages at 7:3 are followed by preventative and corrective maintenance strategy weight percentages at 1:1 (alternative B, weight value 0.244). Finally, the preventative and corrective maintenance strategy weight percentage is at 3:7 (alternative C, weight value 0.149). This result explains that the majority
of rolling stock maintenance work focuses on preventative maintenance. It is dangerous to cease railway system operations for the reason of rolling stock component failure. It seems that a preventive-oriented maintenance strategy could probably assure rolling stock safety. In addition, this empirical result obtains the ratio PM/CM multiplied by the weights of choosing this scenario alternative in order to obtain the $K_1/K_2$ ratio based on the expert decisions for estimating the spare parts of the component.

4.3. Estimation of spare parts

Through the ANP methodology, the railway rolling stock’s preventative maintenance and corrective maintenance ratio is obtained as 7:3, and this ratio is applied to estimate the needed spare parts’ quantities of Taipei’s MRT rolling stock model 321 current collecting shoe. The multi-attribute utility function is applied to estimate spare parts’ quantities.

The PM/CM ratio can vary according to the rolling stock components investigated. The scenario alternative regarding the estimated PM/CM ratio of 7:3 is obtained through the randomly selected 50 sampled data from the historical data of the rolling stock components investigated. This ratio can also be 6:4 or 6.5:3.5. The ratio is sampled data from the historical data of the rolling stock components.

The PM/CM ratio of 7:3 is obtained through the randomly selected 50 sample data from the historical data of the rolling stock components investigated. This ratio can also be 6:4 or 6.5:3.5. The ratio is subjected to the historical maintenance data of the rolling stock components which we would like to investigate. If the ratio is 8:2 instead of 7:3, then this result indicates much more importance of stock components which we would like to investigate. The multi-attribute utility function is applied to estimate spare parts’ quantities.

The probability of an item’s non-supply during the various planning horizons is derived as follows. The ANP empirical result obtains the weight of non-supply when the system operator prepares 2 spare parts during the two-year planning horizon.

Fig. 3. The relationship between accumulated failure rate ($P_f$) and time ($x$) of the selected 50 sample units. The estimation of the probability of the provisioning shortage $x$ in one year with only spare parts available is derived as follows: Provided that the value obtained by the randomly selected 50 sample units with values $\beta=7.5$ and $\theta=13.644$ is adopted and the planning horizon is one year (12 months), Thus, $x=12$ is used for our estimation.

The probability density function of the Weibull failure distribution here is assumed as follows:

$$f(x) = \frac{\beta}{\theta} \left(\frac{x}{\theta}\right)^{\beta-1} \exp\left(-\left(\frac{x}{\theta}\right)^\beta\right)$$

where $x \geq 0$, $\theta > 0$, $\beta \geq 0$, $F(x) = 1 - \exp\left(- \left(\frac{x}{\theta}\right)^\beta\right)$.

<table>
<thead>
<tr>
<th>Year</th>
<th>0 Spare part</th>
<th>1 Spare part</th>
<th>2 Spare parts</th>
<th>3 Spare parts</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.317345</td>
<td>0.0000217639</td>
<td>2.86572 × 10^{-11}</td>
<td>3.106 × 10^{-18}</td>
</tr>
<tr>
<td>2</td>
<td>1.272266</td>
<td>0.00014376</td>
<td>3.209 × 10^{-9}</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.999999</td>
<td>0.236493</td>
<td>0.000359</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.99278</td>
<td>0.20752</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>1</td>
<td>0.991189</td>
<td></td>
</tr>
</tbody>
</table>

The multiple utility function is applied to obtain the maximum utility value after calculating the integration of these two cumulative density functions $F_C$ and $F_F$ and are estimated in Table 5. The cell in Table 5 indicates the probabilities of an item’s non-supply for the preparation of different spare parts during the various planning horizons (year). For example, the cell (2 years, 2 spare parts) of Table 5 reveals that the probability of an item’s non-supply when the system operator prepares 2 spare parts under a two-year planning horizon is 0.00014376.

4.3.1. Multiple utility function

The multiple utility function is applied to obtain the maximum utility value after calculating the $x$ value. The multi-attribute utility function is expressed as follows:

$U(C,x) = K_1 U_F(C) + K_2 U_L(x)$

where $U(x)=\exp(-A_2 x)$ and $U(C)=\exp(-A_2 C)$. $K_1$ is the probability of preventive maintenance; $K_2$ the probability of corrective maintenance. $K_1 + K_2 = 1$, and $K_1$ and $K_2$ values are derived from the ANP result.

The probability of the provisioning shortage $x$ during the various planning horizons is generalized by using the convolution to calculate the integration of ANP empirical result, which is $0.607$ for PM/CM = 7:3, 0.244 for PM/CM = 1:1, and 0.149 for PM/CM = 3:7. This study assumed the current collecting shoe cost as U$100 (U$1 = NT$33). This study also assumes that $A_1 = 16$ and $A_2 = 0.002$ in order to obtain the maximum utility value according to Almeida (2001). The ANP empirical result obtains the weight of non-supply when the system operator prepares 2 spare parts during the two-year planning horizon.

The relationships between preparation of the spare parts’ quantities and the utility value of the multi-attribute utility function under various planning horizons.
4.3.2. Optimum spare parts estimation

According to the result derived from the multiple utility function in Fig. 4, the optimum spare part estimation under various planning horizons can be derived. Our result indicates the system operator needs to prepare at least one spare part when the planning horizon is greater than 7.5 months and two spare parts when the planning horizon is between 7.5 and 19 months. This study follows Almeida (2001) and assumes a one-to-one facility and spare part composition. Therefore, this study assumes that model 321 of Taipei’s mass rapid transit adopts the one-to-one car and current collecting shoe with one train containing 6 cars. In other words, each train must be equipped with 6 spare parts, and thus 36 trains require 216 spare parts when the planning horizon is greater than 7.5 months, but less than 19 months (Fig. 4).

4.4. Optimal replacement interval

This study estimates the optimal replacement interval according to the 50 sample data obtained from Taipei’s mass rapid transit (MRT) after conducting maintenances. The sample data are from 50 random maintenance records of the past maintenance history of Taipei’s mass rapid transit. The results show the average replacement time to be 12.779 months. This study follows Huang et al. (1995) in assuming corrective maintenance is 15 times more than preventive maintenance.

4.4.1. Parameter estimation

Random replacement data show \( Y = \ln(\ln(1 - F(x))) \), and \( X = \ln x \) and obtains the first Weibull distribution failure function linear equation expressed as \( Y = 7.50X - 19.6 \). Through this linear equation, we obtain that the Weibull distribution shape parameter \( \beta \) and scale parameter \( \theta \) are 7.50 and 13.644, respectively. Huang et al. (1995) applied values of these two parameters to obtain the optimal replacement interval.

4.4.2. Replacement interval calculation

This study follows Huang’s et al (1995) mathematical model \( T_s = 0.1 \times T_r \times \theta \) to obtain MRT 321 type rolling stock collecting current shoe’s optimal replacement interval with \( T_s \) as the optimal replacement time. The \( \theta \) value is estimated from 50 random replacement data samples. Replacement time “\( T_r \)” is obtained by following Huang et al. (1995) through the \( \beta \) value and ratio between corrective and preventive maintenance costs. This study adopts the \( \beta \) value of 7.50 and a ratio between corrective and preventive costs at 15:1. Through an estimation graph proposed by Huang et al. (1995), the estimated replacement time \( T_r \) is between 5.0 and 6.0. Therefore, optimal replacement intervals are found to be between 6.8 and 8.2 months. Our empirical results with respect to the estimation of spare parts’ quantities and replacement interval optimization in this present model are considered to be reasonable after seeking the relevant railway rolling stock maintenance experts’ opinions.

5. Conclusion and suggestions

The purpose of this paper is to present an approach for deciding on an appropriate rolling stock maintenance strategy selection and estimating possible spare parts’ quantities and replacement interval for the component of rolling stock. The issue of rolling stock maintenance strategy selection is not just a cost-oriented issue, as it should also consider safety, cost, and quality aspects. The trade-off relationship among these three main factors also increases the complexity of the problem. Thus, the ANP technique can be used to investigate the interrelationship among the factors. The empirical result derived from the ANP can obtain the possible ratio between preventive maintenance and corrective maintenance in order to indicate the possible spare parts’ quantities and replacement interval of the rolling stock components.

The empirical result based on the ANP method regarding rolling stock maintenance strategy selection also indicates that preventive maintenance should be much more valued than corrective maintenance. This result is consistent with the studies of maintenance strategies on industrial equipment (Nakagawa, 1989; Huang et al., 1995; Chelbi and Ait-Kadi, 2001). In addition, the empirical result derived from the ANP method shows that safety is the most crucial factor for rolling stock maintenance strategy selection. Safety here considers not only passenger safety, but also maintenance agent safety. This finding is not consistent with previous studies that focus on industrial facilities and equipment maintenance (Bevilacqua and Braglia, 2000), but is consistent with Wang et al. (2007) who indicated safety as being the most important factor in selecting a maintenance strategy in the chemical industry and power plants. Safety is also essential for rolling stock maintenance. Railway systems cannot risk a break in operations due to the failure of rolling stock components, which could result in possible uncompensated loss of a passenger’s life. The second important factor for rolling stock maintenance strategy selection is about cost and reliability. This means that reducing maintenance cost and avoiding trains idling in the maintenance site are essential for rolling stock maintenance. The third factor affecting the rolling stock maintenance strategy choice by the experts includes maintenance quality and efficiency.

Fig. 4. Estimated utility values for the preparation of different spare parts under various planning horizons.
This proposed approach herein can also assist decision makers in the evaluation and selection of rolling stock maintenance strategies and also in the estimation of component spare parts’ quantities and replacement interval optimization. This study chose Taipei’s MRT rolling stock component, the model 321 current collecting shoe, as an analytical component to estimate spare parts’ quantities under the various planning horizons and optimal replacement interval, because the current collecting shoe is necessary for the daily operation of mass rapid transit systems.

Most previous research studies on rolling stock maintenance do not consider rolling stock maintenance strategy selection and spare part estimation simultaneously. This study’s contribution is in combining a multi-criteria decision-making method, spare part estimation, and a replacement interval model to establish a new systematic approach in order to obtain a suitable rolling stock maintenance strategy and then to produce an estimation of spare parts’ quantity and replacement interval approximation. An advantage to this approach lies in its ability to link safety, cost, and quality, which are the factors associated with selecting an appropriate rolling stock maintenance strategy. Although the ANP technique appears complicated, it can capture the complexity of real world situations for maintenance strategy selections.

In this study, rolling stock maintenance experts suggested the choice of components for spare part optimization and replacement interval estimation analysis. Taipei’s MRT rolling stock model 321 current collecting shoe is taken for analysis, because of its importance for safe operation. In the future, the choice component for analysis can be based on a more objective approach. The critical component of rolling stock operations may be previously determined by the analysis result of failure modes effects and criticality analysis (FMECA) and fault tree analysis (FTA).

References