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An Overall Performance Measure for Vehicle Retirement Decision

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A fleet of vehicles with the same type and age needs to retire at different time points. The problem is to choose a subset of vehicles that will be first retired based on the overall performance of each vehicle. The paper presents an approach to establish an overall performance model based on operational and maintenance data of vehicles. The first step of the approach is to identify the key performance indicators based on the engineering knowledge; the second step is to carry out a principal component analysis so as to reduce the dimension of the problem; and the final step is to establish the overall performance model using the closeness measure of TOPSIS. The approach is illustrated by a real-world example, and the results are compared with the actual retirement decision. It is shown that the model-based decision is fairly consistent with the actual decision.

1. Introduction

The underlying decision variable in vehicle replacement or retirement problems is usually the age of a vehicle (Jorge and Rui, 1997), and the objective function is the total operating cost, which is often assumed to be non-decreasing with age. This assumption may not be true due to the “user preference utilization pattern” that the new vehicles become the most highly utilized so that their operational costs can be higher than those of the older vehicles (Parthana et al., 2012).

There are situations where the age is not the underlying variable of vehicle retirement decision. For example, the vehicles with the same age may be retired at different times due to the acquisition budget constraint as mentioned by Rueda and Miller (1983) and Dietz and Katz (2001). In this case, the performances of individual vehicles have to be evaluated based on technical information and economical information. A large amount of field data in a vehicle fleet management system is available. This makes it possible to evaluate the performance of each vehicle for performance-based retirement decision. Jiang and Shi (2010) deal with this problem based on the correlation and regression analysis. Their approach requires the information of actual retirement decision and this limits its usefulness.

This paper presents a novel approach to improve their approach. The proposed approach includes three steps. The first step is to collect field data and identify key performance indicators (KPIs) based on the engineering knowledge. The second step carries out a Principal Component Analysis (PCA) so as to reduce the dimension of the problem. The third step establishes the overall performance model using the closeness measure of TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). The approach is illustrated by a real-world example, and the results are compared with the actual retirement decision.

The paper is organized as follows. Section 2 gives the background and KPIs of the example. The proposed approach is presented and illustrated in Section 3. The paper is concluded in Section 4.

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2. Background and KPIs

Consider a sub-fleet of 15 vehicles from a mixed postal vehicle fleet. The vehicles under consideration are the same age, type and model. By the time that data were collected 13 vehicles had retired in three lots (see Table 1) and the other two vehicles were in service.

Table 1: Numbers of vehicles retired in different lots

Lot 1	Lot 2	Lot 3	In service
3	1	5	10
4	2	9	12
6	7	15	
8	11		
14	13		

A vehicle management system records cumulative kilometer reading (denoted as k in 10^3 km), cumulative oil-consumption (denoted as l in L), and cumulative maintenance cost (denoted as C_m in 10^3 RMB Yuan) for each vehicle. The maintenance cost includes the costs of repairs, spare part, tyre, etc, but does not include the overhaul cost. The company implements a driver incentive policy to control the fuel consumption and repair costs. The data are updated per 6 months. Jiang and Shi (2010) examine the plot of the cumulative kilometers versus vehicle age, and find that the plot is somehow convex and the lately retired vehicles have relatively large cumulative kilometers. These phenomena are explained by two assumptions: (a) the user wants to sufficiently utilize the vehicles before they retire, and (b) a healthy vehicle is more utilized in the sense of average. The second assumption can be viewed as another kind of "user preference utilization pattern". Based on these assumptions, three additional indicators are considered and they are $\Delta k / \Delta t$, $\Delta l / \Delta k$ and $\Delta C_m / \Delta k$. As such, there are totally six KPIs, and their values at the moment of decision are shown in Table 2.

Table 2: Data of KPIs

Vehicle	Original variables			Derived variables		
	k, 10^3 km	l, L	C_m, 10^3 Yuan	$\Delta k / \Delta t$	$\Delta l / \Delta k$	$\Delta C_m / \Delta k$
1	870.37	143.52	118.38	92.68	0.1134	0.2120
2	863.05	144.83	110.32	99.30	0.1127	0.2195
3	945.68	151.98	111.64	95.25	0.1134	0.3033
4	647.18	96.64	80.97	76.57	0.1126	0.3602
5	800.37	126.95	105.73	85.95	0.1128	0.2934
6	899.41	151.17	119.02	109.15	0.1127	0.1975
7	927.28	150.40	129.63	118.06	0.1133	0.1489
8	794.93	128.75	113.71	113.81	0.1127	0.2618
9	928.47	158.12	107.33	112.50	0.1122	0.2155
10	917.49	155.97	99.27	108.10	0.1130	0.1733
11	937.82	156.36	101.03	110.44	0.1132	0.1849
12	840.37	123.51	70.12	99.01	0.1132	0.0435
13	901.78	143.79	123.48	117.44	0.1133	0.1558
14	936.73	163.89	104.03	119.57	0.1133	0.1549
15	919.62	153.21	111.31	119.47	0.1132	0.1576
μ_j	875.37	143.27	107.06	105.15	0.1130	0.2055
σ_j	79.60	17.55	15.35	13.16	3.61□10^4	0.0770

3. Overall performance model

The problem involves multiple variables and they correlate to some extent. The PCA helps to obtain mutually independent linear combinations of the variables; and the TOPSIS can combine several variables into a distance-based measure. We use these two techniques to build the overall performance model.

3.1 PCA

PCA involves the following multi-step procedure (for more details, see Jolliffe, 2002).

Step 1: Calculate the sample mean and standard deviations for each variable, and standardize the original observations:

$$\mu_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}, \sigma_j^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ij}-\mu_j)^2\ ,\ y_{ij} = \frac{x_{ij}-\mu_j}{\sigma_j} \tag{1}$$

where n is the total number of vehicles, μ_j is the sample mean of the j-th variable, σ_j is the sample standard deviation with $1 \le j \le 6$, x_{ij} is the value of the j-th variable for the i-th vehicle, and y_{ij} is the standardized value of x_{ij}.

Step 2: Calculate the covariance matrix of the standardized observations.

Step 3: Calculate the eigenvalues and unit eigenvectors of the covariance matrix. The eigenvalues are arranged in descending order.

Step 4: Compute the contribution of each eigenvector and select a subset of the principal components.

Step 5: Convert the observed data to component scores and interpret each selected principal component.

PCA can be conveniently carried out using a spreadsheet program such as Excel. For the example in this paper, the sample mean and standard deviations are shown in the last two rows of Table 2; the correlation matrix is shown in Table 3; and the eigenvalues (λ_k, $1 \le k \le 6$) and unit eigenvectors (U_k) are shown in Table 4.

Table 3: Correlation matrix

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
Y_1	1	0.9581	0.4819	0.7075	0.4151	-0.5344
Y_2	0.9581	1	0.5276	0.7205	0.274	-0.4192
Y_3	0.4819	0.5276	1	0.4795	0.1721	0.0551
Y_4	0.7075	0.7205	0.4795	1	0.1955	-0.6118
Y_5	0.4151	0.274	0.1721	0.1955	1	-0.4054
Y_6	-0.5344	-0.4192	0.0551	-0.6118	-0.4054	1

Table 4: Eigenvalues and eigenvectors

k	λ_k	c_k	C_k	U_1	U_2	U_3
1	3.4378	0.5730	**0.5730**	**0.5094**	0.0374	-0.0020
2	1.1465	0.1911	**0.7640**	**0.4927**	0.1831	-0.0953
3	0.8067	0.1344	**0.8985**	0.3087	**0.6359**	0.3290
4	0.4296	0.0716	0.9701	**0.4624**	0.0412	-0.3536
5	0.1555	0.0259	0.9960	0.2591	-0.4343	**0.8195**
6	0.0239	0.0040	1	-0.3485	**0.6086**	0.2935

Let u_{jk} denote the j-th element of the k-th principal component. The k-th principal component is defined as

$$P_k = \sum_{j=1}^{6} Y_j u_{jk} \tag{2}$$

The value of P_k for a particular data point is called the component score and given by

$$s_{ik} = \sum_{j=1}^{6} y_{ij} u_{jk} \tag{3}$$

The contribution of P_k to the total variance is given by

$$c_k = \lambda_k / \sum_{l=1}^{6} \lambda_l \tag{4}$$

The cumulative contribution of the first k principal components is given by

$$C_k = \sum_{l=1}^{k} c_l \tag{5}$$

As such, the information represented by the KPIs can be approximated by the first k principal components if $C_{k-1} < 0.9 \le C_k$. For the example in this paper, we take $k = 3$. The component scores are calculated from (3) and shown in Table 5.
We now look at the interpretation of the three principal components. As seen from Table 4, the first and fourth elements of U_1 (i.e., u_{11} and u_{14}) have relatively large values and correspond to mileage variables. Therefore, P_1 represents the usage. According to the user preference utilization mentioned earlier, it is larger-the-better.
Similarly, the third and sixth elements of U_2 have relatively large values and correspond to maintenance cost variables and hence P_2 represents the maintenance cost with a smaller-the-better nature. The fifth element of U_3 has a very large value and corresponds to fuel consumption variable and hence P_3 represents the fuel consumption. It is also smaller-the-better.

Table 5: Component scores

i	s_{i1}	s_{i2}	s_{i3}	i	s_{i1}	s_{i2}	s_{i3}
1	0.0221	-0.0001	1.5105	9	0.4001	1.2566	-2.0537
2	-0.4544	0.5992	-0.4094	**10**	**0.7185**	**-0.4158**	**-0.4389**
3	0.2831	0.5739	1.5972	11	1.0684	-0.4711	0.0321
4	-5.287	-0.0598	0.1485	**12**	**-0.8613**	**-3.2937**	**-0.6814**
5	**-2.1817**	**0.6149**	**0.4586**	13	1.3859	-0.0175	0.5106
6	0.5771	0.8999	-0.6069	**14**	**1.8617**	**-0.5977**	**-0.0770**
7	1.9115	0.2657	0.563	15	1.5112	-0.2741	-0.0768
8	-0.9551	0.9196	-0.4765				

3.2 TOPSIS
The selected principal components can be fused by the TOPSIS. The start point is the decision matrix $D = \{s_{ij}, 1 \le i \le n, 1 \le j \le k\}$. The normalized performance measure or rating is given by

$$r_{ij} = s_{ij} \Big/ \sqrt{\sum_{i=1}^{n} s_{ij}^2} \tag{6}$$

The matrix $R = \{r_{ij}\}$ is called the normalized decision matrix. Let w_j denote the weight of the j -th criterion (i.e., principal component in this paper). The weighted normalized matrix is defined as $V = \{v_{ij}\} = \{w_j r_{ij}\}$. For the j -th criterion, let

$$v_{jL} = \min(v_{ij}, 1 \le i \le n) ,\ v_{jU} = \max(v_{ij}, 1 \le i \le n) \tag{7}$$

Let $A^+ = (v_j^+, 1 \le j \le k)$ denoted the ideal solution and $A^- = (v_j^-, 1 \le j \le k)$ denoted the negatively-ideal solution. For a larger-the-better [smaller-the-better] criterion, the j -th elements of A^+ and A^- are v_{jU} and v_{jL} [v_{jL} and v_{jU}], respectively.
Let d_i^+ and d_i^- denote the distances of the i -th alternative to the ideal and negatively-ideal solutions, respectively. They are calculated as

$$d_i^+ = \sqrt{\sum_{j=1}^{k} (v_{ij} - v_j^+)^2} ,\ d_i^- = \sqrt{\sum_{j=1}^{k} (v_{ij} - v_j^-)^2} \tag{8}$$

The relative closeness of the i -th alternative with respect to the ideal solution A^+ is defined as below:

$$c_i = 1 / (1 + d_i^+ / d_i^-) \tag{9}$$

The alternatives can be ranked based on the values of ($c_i, 1 \le i \le n$). The best alternative should have the largest value of relative closeness.

A difficult to implement TOPSIS is to specify the criterion weights. In the context of PCA, the criterion weights can be calculated as below:

$$w_j = \lambda_j / \sum_{l=1}^{k} \lambda_l \qquad (10)$$

For the example in this paper, we have (w_j) = (0.6377, 0.2127, 0.1496).

For more details about TOPSIS, see Hwang and Yoon (1981) and Hwang et al. (1993); and a specific application of TOPSIS can be found in Porhinčák and Eštoková (2012).

3.3 Overall performance model

The overall performance model can be defined by (9). A large value of c_i implies a good performance and hence is desired. For the example in this paper, the values of c_i are shown in the second column of Table 6; and the rank numbers of alternatives are shown in the third column. When the number of vehicles to be retired is known, the model-based retirement lot number of a particular vehicle can be determined based on the rank number, and is shown in the fourth column. The last column of Table 6 shows the differences between the model-based and actual lot numbers.

Table 6: Comparison between model-based and actual decisions

i	c_i	Rank	Model-based lot no.	Actual lot no.	Lot difference
1	0.6269	5	1	2	1
2	0.5954	4	1	2	1
3	0.6299	6	2	1	1
4	0.1210	1	1	1	0
5	**0.3967**	**2**	**1**	**3**	**2**
6	0.6765	9	2	1	1
7	0.7498	12	3	2	1
8	0.5371	3	1	1	0
9	0.6627	8	2	3	1
10	**0.7378**	**10**	**2**	**4**	**2**
11	0.7556	13	3	2	1
12	**0.6486**	**7**	**2**	**4**	**2**
13	0.7435	11	3	2	1
14	**0.7991**	**15**	**4**	**1**	**3**
15	0.7728	14	4	3	1

It is noted that eleven of the fifteen vehicles have the lot differences of smaller than or equal to 1, implying that the model-based decision is roughly consistent with the actual decision. This confirms the appropriateness of the proposed approach.

Four vehicles (i.e., Vehicles 5, 10, 12 and 14) have the lot differences of larger than 1. We examine these vehicles one by one as follows.

Referring to Table 5, all the scores of three principal components of Vehicle 5 are poor and hence it should be retired in the first lot. In other words, the model-based decision may be more appropriate.

Vehicle 10 has the 6th largest score in the first principal component and the 5th smallest score in the second and third principal components. As a result, its closeness is very close to the one of Vehicle 13, which was retired in the third lot. In other words, the model-based decision for Vehicle 10 is reasonable.

Vehicle 12 has the 11th largest score in the first principal component, the 1st smallest score in the second principal component and the 2nd smallest score in the third principal component. In other words, it is very poor in the first principal component and very good in the other two principal components so that the model-based decision requires it being retired in the second lot. However, if the vehicle just experienced a high-level preventive maintenance action so that it has a low score in the first principal component, the overall performance model cannot reflect such information and the actual decision is right.

All the scores in the three principal components for Vehicle 14 are good and it should be retired in the last lot. A possible cause for it to be retired in the first lot may be the fact that the decision maker wants to avoid a big upcoming cost such as high-level preventive maintenance.
The above analysis suggests that the vehicle retirement decision should take the maintenance action completed just and upcoming cost into account. Such information can be jointly used with the overall performance model.

4. Conclusions

In this paper we have considered the vehicle performance evaluation problem based on the records of operating and maintenance of vehicles. A hybrid approach that combines PCA and TOPSIS has been proposed to solve this problem. The criteria weights required by TOPSIS can be mathematically generated using the outcomes of PCA. The proposed approach offers a method to fuse KPIs into an overall performance model, and strengthens the capability of TOPSIS to solve multi-criteria decision problems. The approach has been illustrated by a real-world example.
A main conclusion is that the overall performance model can offer fairly reasonable decision and the decision accuracy can be improved through taking the maintenance action completed just and upcoming cost into account. A main finding is that healthy vehicles can be more utilized so that their cumulative kilometers can be higher than those of the unhealthy vehicles.

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