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A Predictive Algorithm for Estimating the Quality of Vehicle Engine Oil

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Recently, with emerging technologies, visibility of vehicle information over the whole lifecycle becomes possible. The visibility opens up new challenging issues for improving the efficiency of vehicle operations. One of the most challenging problems arising during the middle of life (MOL) of vehicles is the predictive maintenance on engine oil. For this, in this study, we focus on developing a predictive algorithm to estimate the quality of the engine oil of a vehicle by analyzing its degradation status with mission profile data. For this purpose, we specify the relations between indicators of engine mission profiles and oil quality indicators using principal component analysis and regression method. Then, we develop a heuristic algorithm for estimating the value of a quality indicator of engine oil based on them. To evaluate the proposed approach, we carry out a case study and computational experiments.

Significance: This study deals with a prognostic maintenance approach for vehicle engine oil, which recently has been highlighted as a cost-effective method using product status data provided by emerging technologies.

Keywords: Predictive maintenance, Degradation, Engine oil, Statistical methods.

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1. INTRODUCTION

Recently, with emerging technologies such as sensors, radio frequency identification (RFID), and mobile tele-communication, it becomes possible to have visibility of vehicle information during its operation. The information visibility gives us new challenging issues for improving the efficiency of vehicle operations. Among them, one of the most challenging issues is predictive maintenance. In general, vehicle maintenance is defined as all technical and managerial actions taken during the usage period to maintain or restore the required functionality of a vehicle. Maintenance strategies can be categorized according to the following three types: breakdown maintenance, preventive maintenance, and predictive maintenance. Predictive maintenance may be similar to preventive maintenance in the sense that its goal is to prevent product abnormality in advance before it occurs. However, the approach of predictive maintenance is different from the time-oriented approach of preventive maintenance. It focuses on degradation monitoring and prediction of degradation process rather than fault detection and diagnostics of components, which is based on the assumption that most abnormalities do not occur instantaneously, and usually there are some kinds of degradation process from normal states to abnormalities (Fu et al., 2004). The monitoring and prediction of a degradation process give us help to identify and solve problems in advance before vehicle damage occurs. In particular, under the new environment where we can easily access and receive vehicle status information in a ubiquitous way, we can predict the deterioration level of vehicle components based on current status of a vehicle. This enables us to do predictive maintenance, i.e. making a prognosis of vehicle status, predicting vehicle's abnormality, and executing proactive maintenance. In spite of its importance, predictive maintenance in vehicle operations has not been considered with much attention in the past. To overcome this limitation, in this study, we deal with the predictive maintenance for engine oil change. Since one of the key points for implementing the predictive maintenance is to develop a predictive algorithm, we focus on developing a predictive algorithm to estimate the quality of the engine oil of a vehicle by analyzing its degradation status. For this purpose, first, we will review previous works that have dealt with predictive maintenance, especially, related to engine oil analysis and methods or algorithms to predict the quality of engine oil. Then, we will develop an analysis method for detecting the degradation status of engine oil. To know

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the status of engine oil, oil analysis can be done by extracting oil samples directly and examining them. This can allow monitoring the amount of contamination, wear rates, and the physical characteristics of engine oil. But, it is time-consuming and costly to get oil samples from an engine directly and analyze them. Hence, instead of it, it is better to use indicators of engine mission profile that can be easily gathered by sensors or on-board vehicle computer without extracting oil samples. Hence, in this study, we analyze the mission profile of a vehicle engine to estimate the degradation status. For this, we specify the relations between indicators of engine mission profiles and oil quality indicators using the principal component analysis and regression methods. In analyzing the relation, we consider usage styles of a vehicle by analyzing mission profile data. Then, we develop a heuristic algorithm for estimating the quality of engine oil. To evaluate and validate the proposed approach, we carry out a case study and computational experiments. The results show that our approach can predict the quality of engine oil effectively by just analyzing mission profile data.

The rest of the paper is organized as follows: In Section 2, we review previous research. We introduce the concept of engine oil degradation and mission profile in Section 3. In Section 4, we propose a predictive maintenance algorithm. In Section 5, we introduce a case study and computational experiments. Finally we conclude our paper with discussion and further research topics.

2. PREVIOUS RESEARCH

There have been many research works about maintenance policies. For example, Bevilacqua and Braglia (2000) classified the maintenance policies into five categories: corrective maintenance, preventive maintenance, opportunistic maintenance, condition-based maintenance, and predictive maintenance. In this study, we focus on predictive maintenance. There have been several publications about predictive maintenance so far. For example, Fu et al. (2004) proposed a predictive maintenance framework for a hydroelectric generating unit. They presented the concept of three key elements for predictive maintenance such as monitoring and forecasting, diagnosis and prognosis, and decision-making. Moreover, Bansal et al. (2004) described a real-time predictive maintenance method for machine systems. They used a neural network approach to predict the parameters of a machine. In addition, Carnero (2005) presented a selection method of diagnostic techniques and instrumentation in a predictive maintenance program. They combined factor analysis and the analytic hierarchy process to develop the method; and applied it to screw compressors. McKendall Jr. et al. (2008) proposed a simulated annealing heuristic for resolving scheduling of maintenance activities at Nuclear power plant. Since the resources required to perform maintenance activities are very limited, they dealt with this problem as a resource constrained project scheduling problem. Recently, predictive maintenance research has been highlighted with the concept of e-maintenance, product identification technologies, and tele-communication technologies. For example, Koç and Lee (2001) addressed the concept of web-enabled predictive maintenance in an intelligent e-maintenance system which is implemented via Internet and showed its system elements. Hiraoka et al. (2003) described the schema and requirements for the part agent that makes a recommendation on the part maintenance based on the gathered information from the Internet and historical data. In addition, Djurdjanovic et al. (2003) proposed a watchdog agent framework for predictive condition-based maintenance by multi-sensor assessment and prediction of machine or process performance. The concept of watchdog agent based its degradation assessment on the readings from multiple sensors that measure critical properties of the process or machinery under a networked and tether-free environment. On the other hand, there have been some publications regarding predicting and evaluating the automotive quality. For instance, Lu (1998) proposed a reliability prediction method to identify vehicle components that have the potential to become actionable items such as a recall system based on early field failure data. Celentano et al. (2004) provided a method to perform a statistical analysis of automotive braking system with statistical characterizations of components and physical-functional relationships of components. Some of them have dealt with research works related to engine oil analysis and its predictive maintenance, which is the subject of this study. For example, Jagannathan and Raju (2000) presented a hybrid approach of predicting the quality and remaining useful life of engine oils for industrial and automotive applications. Youngk et al. (2000) investigated the effectiveness of oil change from the viewpoint of preventive maintenance. They contended that frequent oil changes could reduce the expected life of a vehicle engine. Moreover, Preethichandra and Shida (2000) designed a multifunctional sensor to measure viscosity, cleanness, temperature, and capacitance of engine oils for making a clear decision on their condition.

Although many publications have considered predictive maintenance and engine oil relevant maintenance problems, however, they have some limitations. First, there is a lack of research to address the issue of predictive maintenance about engine oil. Even though some works mentioned engine oil analysis, only a few works dealt with its predictive maintenance. Moreover, in spite of many previous publications that dealt with direct engine oil analysis, little attention has been paid to the research that deals with how to use mission profile data gathered by product identification technologies in predictive maintenance. Hence, there is no explicit guidance about how the quality of engine oil could be estimated considering its usage mode. To cope with these limitations, we focus on developing a predictive algorithm for estimating the quality of engine oil considering engine mission profile.

3. ENGINE OIL QUALITY AND MISSION PROFILE

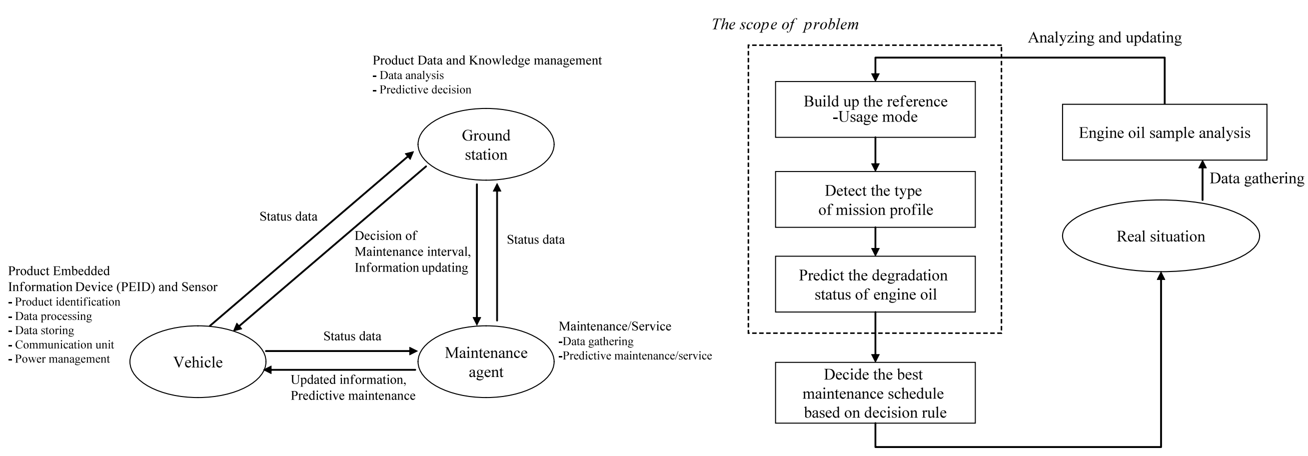
In general, engine oil takes a role of the lifeblood of an engine. It lubricates the engine to reduce the friction between impacting parts. It also cools various engine parts such as crankshaft bearings and pistons. In addition, it cleans the engine and gives some aid in preventing the corrosion of engine parts. Engine oil degradation is a chemical deterioration of the engine oil. It is caused by the base oil combining with oxygen, sulfur, and nitrogen to form harmful compounds. It can also be caused by additive depletion due to reactions with contaminants such as heat, air, metal particles, soot, fuel, and glycol. The process of oil degradation is complex but it can be measured by several indicators. Jagannathan and Raju (2000) mentioned oil quality indicators to identify the degradation status of engine oil.

These indicators can be directly obtained by sampling engine oil or installing relevant sensors. However, these approaches are very time-consuming and high-cost. Hence, to cope with these limitations, we use indirect measures such as engine mission profile (e.g. mileage, number of engine start-up, etc.) which are more cost-effective and time-effective. Indicators for engine mission profile can be easily gathered by product embedded information devices such as sensors and on-board vehicle computers. By analyzing these indicators, we can identify the operation environment of a vehicle, i.e., vehicle usage information. Then, we specify the relations between mission profile indicators and engine oil quality indicators. Based on them, we can predict the degradation status of engine oil more precisely with several statistical methods such as principal component analysis and regression analysis. This is a cost and time effective approach because we can predict the abnormal status of engine oil without extracting engine oil directly by just analyzing indirect indicators that are relative easy to be gathered. This is the basic concept of the predictive algorithm that we propose in this study.

4.PREDICTING ENGINE OIL QUALITY

In this section, before describing our problem, we assume the following:

1) We consider a truck as a tested vehicle in this problem.
2) A truck has product embedded information devices (PEIDs) such as sensors and on-board vehicle computers to gather mission profile data and oil quality indicators.
3) We consider two types of truck mission profiles: urban mode and highway mode.
4) Automatically gathered mission profile data are transmitted to a ground station for analysis by maintenance agents. It will be done periodically at a certain time interval. Hence, we can assume that we know historical data of mission profile and engine oil quality indicators.
5) Data patterns of quality indicators or mission profile indicators have similar features in shape. They are not big different depending on the types of usage mode.



(a) Predictive maintenance envrionment

(b) Overall framework of predictive maintenance algorithm

Figure 1: Predictive maintenance environment and our approach

Figure 1-(a) shows the overall framework for predictive maintenance of a truck. In this framework, three main actors are involved: vehicle, ground station, and maintenance agent. The vehicle (truck) has PEIDs and sensors to gather the status

data of components. The data gathered by sensors will be stored in the PEID. The maintenance agent at the garage has some information devices such as personal digital assistance (PDA) with mobile phone function to transmit gathered data of PEID to a ground station. The ground station will store and analyze gathered data, and decide a suitable predictive maintenance strategy. The ground station will inform the maintenance agent of the predictive maintenance information such as schedule. The maintenance agent will do suitable maintenance actions according to suggestions of the ground station. If necessary, the ground station can directly request the vehicle to call for detailed overhaul.

4.1 Problem description

The goal of our problem is to predict the quality of engine oil of a truck considering gathered mission profile data. If we wonder about the degradation status of engine oil at a specific time, how can we estimate the value of a quality indicator without oil sample analysis, just using historical reference data and the mission profile data gathered until the specific time? This is the problem that we want to solve in this study. To describe our approach, we use the following notations.

A_U and A_H :	Correlation matrices of urban and highway mission profile
D_U , D_H and D_R :	Mission profile matrices of urban, highway and a test truck
E :	Eigenvector
m :	The number of mission profile indicators
P_U , P_H and P_R :	Principal component matrices of urban, highway, and a test truck
t :	Index of time event, t = 1, …, T
V :	Oil viscosity indicator
V_U , V_H and V_R :	Oil viscosity values measured during urban, highway, and a test truck driving
X_{tj} :	Value of mission profile indicator j of a test truck at tth sampling time, t = 1, …, T, j = 1, …, m
Y :	Oil quality indicator
Y_U , Y_H and Y_R :	Values of a quality indicator measured during urban, highway, and a test truck driving
Y_{U_t} , Y_{H_t} and Y_{R_t} :	tth values of a quality indicator measured during urban, highway, and a test truck driving, t = 1, …, T
α_{tj} :	Value of urban mission profile indicator j at tth sampling time, t = 1, …, T, j = 1, …, m
β_{tj} :	Value of highway mission profile indicator j at tth sampling time, t = 1, …, T, j = 1, …, m
χ :	Degree of fitness
δ:	Principal component factor that has a meaningful eigenvalue
L:	Mileage
S:	Number of start-ups
O:	Duration time during which the oil temperature is hotter than 95 °C
W:	Duration time during which the temperature of cooling water is hotter than 80 °C
M:	Duration time during which RPM is greater than 5000

4.2 Predictive algorithm

The algorithm for estimating the quality of engine oil consists of two parts: One is for building up reference data for identifying the mission profile type. The other is for predicting the degradation status of engine oil based on this reference data. To solve our problem, we first build up the reference data which specify the relation between an engine oil quality indicator and mission profile indicators. This reference data will be separately generated according to the type of mission profile. Based on them, we will estimate the engine oil quality with a heuristic method and the regression analysis method. The overall framework is depicted at Figure 1-(b). The detailed algorithm is as follows:

1. Building up reference data

Step 1 : Gather historical data of mission profile indicators and oil quality indicators. In this step, we gather two types of mission profile data and oil quality data: *Urban* (U) and *Highway* (H). Let them as follows.

$$D_U = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1m} \\ \alpha_{21} & \ddots & & \vdots \\ \vdots & & \ddots & \\ \alpha_{T1} & \cdots & & \alpha_{Tm} \end{bmatrix},\ Y_U = \begin{bmatrix} y_{U_1} \\ y_{U_2} \\ \vdots \\ y_{U_T} \end{bmatrix},\ D_H = \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1m} \\ \beta_{21} & \ddots & & \vdots \\ \vdots & & \ddots & \\ \beta_{T1} & \cdots & & \beta_{Tm} \end{bmatrix},\ Y_H = \begin{bmatrix} y_{H_1} \\ y_{H_2} \\ \vdots \\ y_{H_T} \end{bmatrix}$$

Step 2 : Calculate the correlation matrix of D_H and denote it as A_H.

$$A_H = \begin{bmatrix} 1 & & \cdots & & \gamma_{1m} \\ & 1 & & \gamma_{ij} & \\ & \gamma_{ji} & \ddots & \vdots & \\ & \vdots & & 1 & \\ \gamma_{m1} & & \cdots & & 1 \end{bmatrix} \text{ where } \gamma_{ij} = \gamma_{ji} = \begin{cases} \dfrac{\sum_{k=1}^{T}(\beta_{ik} - \overline{\beta_i})(\beta_{jk} - \overline{\beta_j})}{\sum_{k=1}^{T}(\beta_{ik} - \overline{\beta_i})^2 \sum_{k=1}^{T}(\beta_{jk} - \overline{\beta_j})^2}, & \text{if } i \neq j \text{ and } 1 \leq i < j \leq m \\ 1, & \text{if } i = j \end{cases}.$$

Here $\overline{\beta_i}$ and $\overline{\beta_j}$ imply the time average of β_i and β_j, respectively (Mood et al., 1974).

Step 3 : Compute eigenvectors and eigenvalues for A_H. Using A_H, we compute the eigenvectors E_H and eigenvalues. The eigenvalues tell us how many principal component factors are needed to explain our data. In this study, according to the *Kaiser-Guttman* rule (Gorsuch, 1983), we pay attention to the eigenvalue that is bigger than 1. Denote it as δ, $\delta \in \{1, \ \ldots, i^*\}$.

Step 4 : Calculate the principal component data, P_H and P_U, using the eigenvectors, E_H ($m \times m$ matrix) as follows: $P_H = D_H \cdot E_H$, $P_U = D_U \cdot E_H$. Here we use E_H in the calculation of P_U for consistency of the comparison.

Step 5 : For a meaningful principal component factor, δ, $\delta \in \{1, \ \ldots, i^*\}$, calculate $\chi_{U\delta}$ which indicates the degree of fitness of urban data to highway data. For this, let $\chi_{U\delta} = \left(\sum_{t=1,\ldots,T} p_{t\delta}^U / p_{t\delta}^H \right) \Big/ T$ where T indicates the number of observed values; and $p_{t\delta}^U$ and $p_{t\delta}^H$ indicate the (t, δ)th component of P_U and P_H, respectively. This value is used as a reference data to identify the type of mission profile (see step 3 of the next algorithm).

Step 6 : Build up regression models about a quality indicator. For each quality indicator Y, we can estimate a regression model for highway mission profile as follows: $Y_H = a_{H0} + a_{H\delta} \cdot P_{H\delta} + b_{H\delta} \cdot P_{H\delta}^2$, $\delta = 1, \ \ldots, i^*$ where a_{H0} , $a_{H\delta}$ and $b_{H\delta}$ are the regression parameters of highway mission profile, δ indicates an element of the set of meaningful principal component factors, $\{1, \ldots i^*\}$, and $P_{H\delta}$ are the principal component vector ($T\times1$ size) for the factor δ in highway mission profile data. In a same way, we can estimate a regression model for urban mission profile as follows: $Y_U = a_{U0} + a_{U\delta} \cdot P_{U\delta} + b_{U\delta} \cdot P_{U\delta}^2$, $\delta = 1, \ \ldots, i^*$

Based on this reference data, we can predict the value of a quality indicator of engine oil using the following algorithm.

2. Predicting the value of a quality indicator of engine oil

Step 1 : Gather data of mission profile indicators of a truck until the current time T^* and denote them as D_R.

$$D_R = \begin{bmatrix} X_{11}, & X_{12}, & \cdots & X_{1m} \\ X_{21} & & & \\ \vdots & & \ddots & \vdots \\ X_{T^*1} & & \cdots & X_{T^*m} \end{bmatrix}$$

Step 2 : Compute the principal component factors based on the mission profile data. Using the eigenvectors E_H, we calculate the principal component data P_R using $P_R = D_R \cdot E_H$.

Step 3 : For each δ, calculate $\chi_{R\delta}$ for comparing with the reference data. Using $P_{R\delta}$, we can calculate $\chi_{R\delta}$ as follows: $\chi_{R\delta} = \left(\sum_{t=1,\ldots,T^*} p_{t\delta}^R / p_{t\delta}^H \right) \Big/ T^*$, $\delta = 1, \ \ldots, \ i^*$ where $p_{t\delta}^R$ indicates the (t, δ)th component of P_R.

If $\chi_R = \sum_{\delta=1}^{i^*} \chi_{R\delta} \Big/ i^*$ is close to $\chi_U = \sum_{\delta=1}^{i^*} \chi_{U\delta} \Big/ i^*$, then we can assume that the test truck has urban mission profile.

If χ_R is close to 1, then we can conclude that its usage mode follows the highway mission profile.

Step 4 : Calculate regression parameters and generate the prediction model of a quality indicator, Y.

$$Y_R = a_{R0} + a_{R\delta} \cdot P_{R\delta} + b_{R\delta} \cdot P_{R\delta}^2, \ \delta = 1, \ \ldots, i^*.$$

The regression parameters a_{R0}, $a_{R\delta}$, and $b_{R\delta}$ can be estimated with the following formulae because we assume that shape patterns of engine oil quality indicators are not big different according to the types of mission profile: For $\delta = 1, \ldots, i^*$,

$$a_{R0} = \frac{a_{U0} - a_{H0}}{i^* - \sum_{\delta=1,\ldots,i^*} \chi_{U\delta}} (i^* - \sum_{\delta=1,\ldots,i^*} \chi_{R\delta}) + a_{H0}, \ a_{R\delta} = \frac{a_{U\delta} - a_{H\delta}}{1 - \chi_{U\delta}} (1 - \chi_{R\delta}) + a_{H\delta}, \text{ and } b_{R\delta} = \frac{b_{U\delta} - b_{H\delta}}{1 - \chi_{U\delta}} (1 - \chi_{R\delta}) + b_{H\delta}.$$

Step 5 : With the prediction model, estimate the value of a quality indicator Y at T^*. Using the (T^*, δ)th value of $P_{R\delta}$, we can estimate Y_R at T^* like this: $Y_{R_{T^*}} = a_{R0} + a_{R\delta} \cdot p^R_{T^*\delta} + b_{R\delta} \cdot (p^R_{T^*\delta})^2$, $\delta = 1, \ldots, i^*$.

5. CASE STUDY AND COMPUTATIONAL EXPERIMENTS

In this section, to show the effectiveness of our approach, we introduce a case study and computational experiments. We generate examples based on several references provided by previous literature (Basu et al., 2000) and a real sample data of an automobile company (IVECO, 2004). Considering patterns of reference data, we generated mission profile data and oil quality data. For statistical analysis methods such as principal component analysis and regression analysis, we use a commercial statistical software. The mission profile data that we consider are five (L, S, O, W, M). As a quality indicator of engine oil, we consider viscosity since it is the most representative quality indicator. The underlying assumptions on the generated mission profile data are as follows:

1) The mileage of a highway mission profile is bigger than that of an urban mission profile at the same period.
2) The urban mission profile has a higher number of engine start-ups compared to a highway mission profile.
3) For the case of RPM, oil temperature, and water temperature relevant data, the highway mission profile has greater values than the urban mission profile does.
4) We assume that the degree of variation of the viscosity value is greater in the urban mission profile than in the highway mission profile, which is a commonly known fact.

5.1 Case study

Current PMTSs have been developed based on the original research work of Frank B. and Lillian M. Gilbreth. The PMTS can be classified the complexity of the elemental levels. There are two distinct levels of classification: Basic-level Systems and High-level Systems. The basic level systems consist of elements which are mostly of single motion and cannot be further sub-divided. Combining two or more basic level elements into a multi-motion element we can obtain higher level systems (Salvendy, 1982).

1. Building up reference data

Step 1 : Gather mission profile data and oil quality data. For this purpose, we generate an example that has 100 sampling data of mission profile indicators and the oil viscosity indicator (see Figure 2).

$$\begin{array}{ccccc} L & S & O & W & M \end{array}$$
$$D_U = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 83.3 & 6 & 7.0 & 1.6 & 1.3 \\ 162.0 & 23 & 7.2 & 3.6 & 2.3 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 5030.8 & 3023 & 116.5 & 124.7 & 69.3 \end{bmatrix}, Y_U = \begin{bmatrix} 0.02 \\ 0.07 \\ 0.16 \\ \vdots \\ 6.24 \end{bmatrix}, D_H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 141.8 & 8 & 5.5 & 9.6 & 1.5 \\ 309.3 & 21 & 5.8 & 13.5 & 2.2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 10935.1 & 1010 & 252.9 & 303.2 & 196.5 \end{bmatrix}, Y_H = \begin{bmatrix} 0.16 \\ 0.19 \\ 0.12 \\ \vdots \\ 4.76 \end{bmatrix}$$

Step 2 : Calculate the correlation matrix, A_H. Because we use only the eigenvectors matrix of highway mission profile data for comparison, we calculate the correlation matrix, A_H.

Step 3 : Calculate the eigenvalues and eigenvectors of the matrix A_H.

Step 4 : Calculate the principal component vector. We get principal component vectors P_H and P_U as follows.

$$P_H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 74.74 & -57.95 & 15.52 & 85.03 & 62.53 \\ 157.71 & -128.60 & 29.15 & 191.29 & 135.28 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 5681.63 & -4432.39 & 849.22 & 6913.62 & 4510.66 \end{bmatrix}, P_U = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 44.50 & -29.37 & 7.45 & 52.58 & 37.01 \\ 88.82 & -62.21 & 13.17 & 106.05 & 60.74 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 3745.43 & -1921.58 & 342.78 & 4080.24 & -32.73 \end{bmatrix}.$$

Step 5 : Calculate the degree of fitness, χ. Because the first component among the eigenvalues explains most of the data (99.44%), we use only the first column vectors of P_H and P_U in calculating χ, i.e. $\delta = 1$. Denote them as P_{U1} and P_{H1}, respectively. Then, we can calculate $\chi_{U1} = 0.635$.

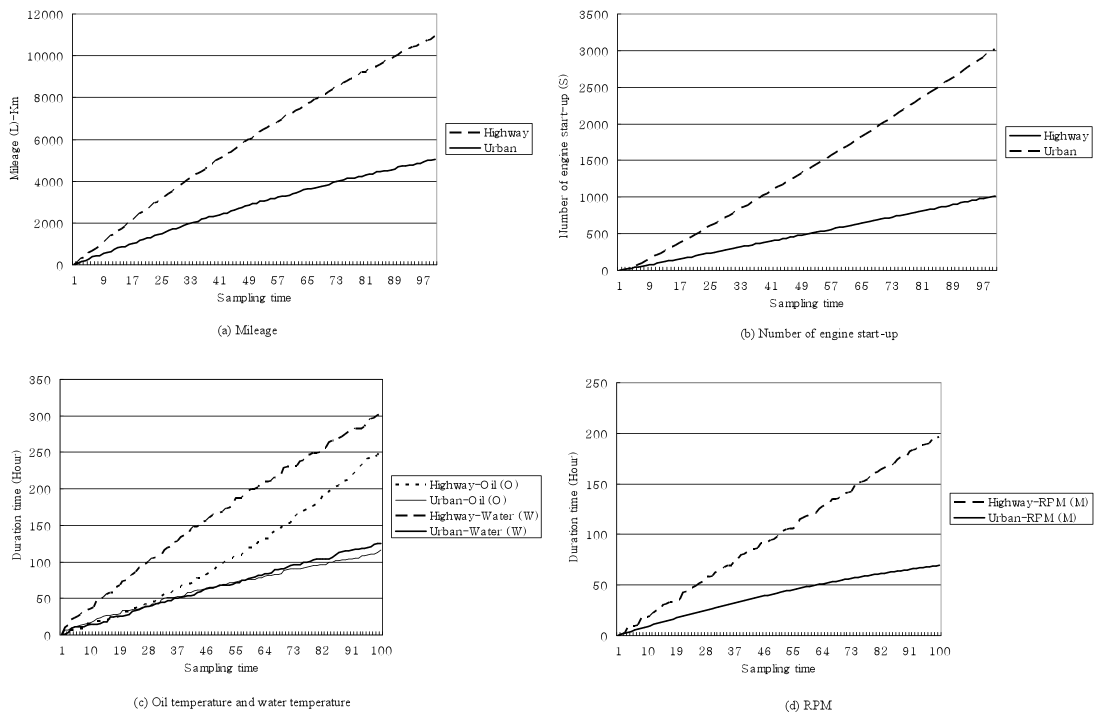


Figure 2: Data of mission profile indicators

Step 6 : Build up the regression model about the viscosity. Using a commercial statistical software, we could get a multiple regression model as follows: $V_H = 0.29831 - 0.00031445 \cdot P_{H1} + 1.913206 \cdot 10^{-7} \cdot P_{H1}^2$. In this case, *R-square* is 0.9971 which indicates that our regression model represents the relation of data well. In a same way, we could estimate a regression model for urban mission profile using the same eigenvectors as follows: $V_U = 0.13879 + 0.00111 \cdot P_{U1} + 1.332088 \cdot 10^{-7} \cdot P_{U1}^2$. In this case, *R-square* is 0.9988. Figure 3 shows the plot between the regression model (dotted line) and the measured viscosity data (solid line) for the highway and urban mission profiles. From this Figure, we can see that our model matches well with real data.

So far we have dealt with how to build up the reference data. From now on, based on the reference data, we predict the quality of engine oil using the following algorithm.

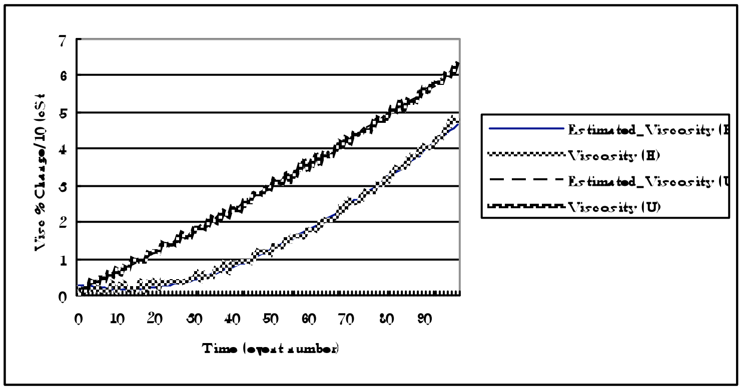


Figure 3: Viscosity data in highway mission profile

2. Predicting the value of a quality indicator of engine oil

Step 1 : For taking an example, we generated a small-sized example until 7th sampling, D_R.

Step 2 : Since the reference data uses only the first principal component factor, we calculate P_{R1} as follows:

$$P_{R1} = D_R \cdot E_{H1} = \begin{bmatrix} 0.0 & 0 & 0.0 & 0.0 & 0.0 \\ 160.7 & 10 & 18.3 & 1.1 & 9.4 \\ 175.2 & 56 & 19.0 & 4.7 & 14.4 \\ 304.9 & 101 & 20.0 & 11.8 & 19.3 \\ 339.1 & 147 & 25.3 & 13.0 & 24.3 \\ 435.7 & 189 & 28.5 & 13.1 & 29.3 \\ 548.3 & 232 & 33.6 & 17.8 & 34.3 \end{bmatrix} \cdot \begin{bmatrix} 0.455 \\ 0.448 \\ 0.433 \\ 0.443 \\ 0.456 \end{bmatrix} = \begin{bmatrix} 0.0 \\ 90.46 \\ 121.55 \\ 206.47 \\ 247.74 \\ 314.54 \\ 391.30 \end{bmatrix}.$$

Step 3 : To know the type of mission profile of the test truck, we calculate χ_{R1}. If χ_{R1} is close to *1*, the mission profile of a test truck can be regarded as the highway mission profile. On the contrary, if χ_{R1} is close to 0.635, then we can conclude that the mission profile of a test truck is similar to the urban mission profile. In this case, since $\chi_{R1} = 0.97$, we can see that the mission profile data that we gathered is very similar to the highway mission profile.

Step 4 : Calculate the regression parameters. With $\chi_{R1} = 0.97$, we could estimate the following: $a_{R0} = 0.285198$, $a_{R1} = -0.000197$, and $b_{R1} = 0.000000$. Then, we can get the following model: $V_R = 0.285198 - 0.000197 \cdot P_{R1}$

Step 5 : With the following model, we estimate the viscosity value at the current time T^*=7: $V_{R_7} = 0.285198 - 0.000197 \cdot p_{71}^R$. Since $p_{71}^R = 391.30$, the estimated viscosity value is about 0.208. It is a reasonable value when compared with the viscosity value (0.145) of highway mission profile.

This case study shows that we can estimate a meaningful value of an engine oil quality indicator based on the analysis of reference data if we can know the mission profile data at the certain time.

5.2 Computational experiments

To validate the effectiveness of our algorithm in a more complete way, computational experiments were done on a number of test problems. For the experiments, 30 test examples were generated randomly. We generated 10 data sets based on the data of previous literature that we mentioned earlier. For each data set, we made the data into three groups which indicate 25th, 50th, and 75th sampling data, respectively.

Since we do not know the future value of viscosity in advance, the estimated values of the suggested algorithm were compared with the viscosity values that we can estimate by regression analysis when we just know the mileage information. For the comparison, we use relative performance measures called the relative performance ratio 1 (RPR1) and relative performance ratio 2 (RPR2) for each problem, which are defined as $(S_a - S_{T1}) \cdot 100 / S_a$ and $(S_a - S_{T2}) \cdot 100 / S_a$, respectively. Here, S_a is the estimated value obtained from our algorithm, S_{T1} is the estimated value obtained by simple regression analysis just using mileage as an independent variable and viscosity as a dependent variable without considering mission profile type, and S_{T2} is the value of regression models considering mission profile type. For S_{T2}, we made two regression models considering mission profile type: a highway regression model and an urban regression model, and used the models to estimate the viscosity values of suitable examples. If the value of degree of fitness (χ) of an example is more than 0.8175, then we used the highway mission model, otherwise, vice versa. The RPR index reflects how well a particular our algorithm performs relative to other simple methods. Table 1 shows the relative performance ratio between our algorithm and other simple regression methods. This table shows that there is a certain amount of difference between the estimated values of our algorithm and others. Average RPRs indicates that the values of our algorithm have about 50% or 90% relative difference with those of RPR2 or RPR1. This does not directly mean that our algorithm outperforms others about 50 or 90% because we do not know the real viscosity values until we do direct oil sampling analysis. However, as we can easily expect that RPR2 will outperform RPR1 because it considers mission profile type, we can conclude that our algorithm gives better estimation values than others.

From the results, we could conclude that our approach provides a simple but efficient tool to predict the engine oil quality without direct oil sampling analysis. Nevertheless, there are some limitations which can be considered in further research. First, our algorithm focuses on only one quality indicator. Because several factors can affect the quality of engine oil during vehicle operations, it is necessary to identify critical indicators of engine oil quality that have close relations with the degradation status of engine oil. Furthermore, to decide the oil degradation status in a more precise way, simultaneous analysis of many quality indicators is needed. Second, there is a lack of support for the decision for engine oil change. Although our algorithm provides the estimated value of a quality indicator based on gathered mission profile data, there is no guidance about when oil should be changed. In addition, it is necessary to consider not only two kinds of mission profile types but also more ones in the estimation algorithm. In spite of these limitations, we believe that our study has proposed a simple but efficient method to predict the status of an oil quality indicator based on mission profile data.

Table 1: Experimental results

Test data ($D^\dagger$, $T^\ddagger$)	Degree of fitness (χ)	Estimated value (S_a)	Estimated value (S_{T1})	Estimated value (S_{T2})	*RPR1*♠	*RPR2*♦
(*D1, 25th*)	0.86	0.94	2.89	0.22	206.85	77.02
(*D1, 50th*)	0.88	2.01	2.70	0.78	34.43	61.31
(*D1, 75th*)	0.88	3.61	0.37	1.80	89.62	50.22
(*D2, 25th*)	0.97	0.37	2.71	0.19	638.16	47.37
(*D2, 50th*)	0.91	1.58	3.00	0.63	89.69	60.25
(*D2, 75th*)	0.88	3.16	1.14	1.35	63.87	57.38
(*D3, 25th*)	0.94	0.51	2.74	0.20	434.93	61.65
(*D3, 50th*)	0.89	1.73	3.03	0.61	74.79	64.72
(*D3, 75th*)	0.87	3.33	1.02	1.38	69.26	58.43
(*D4, 25th*)	0.77	1.13	2.43	2.01	114.63	77.70
(*D4, 50th*)	0.76	2.54	3.20	4.58	26.38	80.51
(*D4, 75th*)	0.77	4.05	2.14	7.36	47.29	81.72
(*D5, 25th*)	0.82	0.99	2.53	0.18	156.65	81.85
(*D5, 50th*)	0.80	2.30	3.17	4.81	37.85	109.25
(*D5, 75th*)	0.79	3.76	2.04	7.52	45.79	99.97
(*D6, 25th*)	0.64	1.33	1.40	1.17	5.73	11.64
(*D6, 50th*)	0.63	2.85	2.79	2.50	1.84	12.07
(*D6, 75th*)	0.63	4.42	3.22	3.84	27.11	13.08
(*D7, 25th*)	0.79	1.08	1.78	1.43	65.64	32.66
(*D7, 50th*)	0.78	2.43	3.02	2.96	24.05	21.47
(*D7, 75th*)	0.78	4.14	3.18	4.74	23.22	14.30
(*D8, 25th*)	0.70	1.23	1.34	1.13	8.65	7.97
(*D8, 50th*)	0.68	2.66	2.61	2.23	1.96	16.19
(*D8, 75th*)	0.67	4.23	3.12	3.25	26.35	23.17
(*D9, 25th*)	0.92	0.64	2.15	0.17	235.68	74.22
(*D9, 50th*)	0.91	1.84	3.22	0.35	75.18	80.92
(*D9, 75th*)	0.92	3.49	2.70	0.78	22.71	77.60
(*D10, 25th*)	0.80	1.04	1.49	1.23	43.20	17.88
(*D10, 50th*)	0.79	2.43	2.80	2.51	15.16	3.33
(*D10, 75th*)	0.80	4.02	3.22	3.87	19.85	3.85
				Average of *RPRs*	90.88	49.32

† Datat set, ‡ Time point, ♠ Relative performance ratio 1: $(S_a - S_{T1}) \cdot 100 / S_a$, ♦ Relative performance ratio 2: $(S_a - S_{T2}) \cdot 100 / S_a$

6. CONCLUSION

In this study, we have proposed a predictive algorithm to estimate the value of a quality indicator of engine oil based on mission profile data. In the proposed method, we analyzed the relation between indirect indicators and direct indicators with statistical analysis. We applied principal component analysis to our approach for finding the main factors among the indirect indicators (mission profile parameters) which have close relations with the oil quality. For identifying the relation between an oil quality indicator and mission profile parameters, we used regression models. Based on the regression model, we predicted the engine oil status. Our approach is useful in the sense that we do not need to extract oil samples directly and analyze them for diagnosing the status of engine oil. Eventually, our algorithm can be the basis for increasing the usage life, the availability, and performances of an engine of a vehicle. Although our work may not provide an exhaustive result about predictive maintenance of engine oil, we think that our work has laid the cornerstone for predictive maintenance of engine oil. As further research issues, one can consider developing a decision algorithm that informs us of the best changing interval of engine oil. Moreover, one can define the complex inter-relations among quality indicators or among mission profile indicators or between them in detail, and can develop analytical approaches to predict the quality of engine oil.

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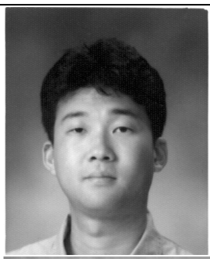

BIOGRAPHICAL SKETCH

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