

A New Method for Bus Drivers' Economic Efficiency Assessment

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ABSTRACT

Transport vehicles consume a large amount of fuel with low efficiency, which is significantly affected by drivers' behaviors. An assessment system of eco-driving pattern for buses could identify the deficiencies of driver operation as well as assist transportation enterprises in driver management.

This paper proposes an assessment method regarding drivers' economic efficiency, considering driving conditions. To this end, assessment indexes are extracted from driving economy theories and ranked according to their effect on fuel consumption, derived from a database of 135 buses using multiple regression. A layered structure of assessment indexes is developed with application of AHP, and the weight of each index is estimated. The driving pattern score could be calculated with these weights. Meanwhile, allowing for the impact of vehicles and roads, the system trains an artificial neural network with excellent drivers' driving data in order to predict the ideal fuel consumption of specific maneuvers. The driving pattern score can be validated with the fuel score that is obtained from the comparison between actual and ideal fuel consumption. Finally, an assessment system of eco-driving patterns for transport vehicles is established. The results show potential of this system to be used in big-data from connected vehicles in the future.

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INTRODUCTION

Commercial vehicles account for a large part of energy consumption in spite of their small portion of the total vehicle population. In 2009, almost 30% of the fuel consumption came from commercial vehicles, which only represented 5.8% of the total vehicles within China. Thus, the government and public have been looking for methods to improve their driving efficiency. It is acknowledged that fuel economy is affected by three key factors: driver, route and vehicle. There can be more than a 10% difference in fuel consumption between eco-drivers and average drivers [1, 2]. Thus, the concept of eco-driving has been proposed in past decades all over the world to encourage drivers to exhibit more environmentally-friendly behaviors. As for fleet management, an enterprise's transport efficiency greatly depends on the individual fuel efficiency of its staff. And the large amount of running data obtained from daily operations is of great value for analyzing the driving patterns.

Numerous researchers have studied assessment methods for understanding the economics of a driver's behavior. Bharathi Krishnamoorthy et al. analyzed the trip data obtained from Fleet Management Systems with an application of Six Sigma methods to identify the key factors impacting fuel efficiency [3]. A number of events such as excessive idling were used to calculate Parts per Million, implying the defects of driving behaviors. D Vangi et al. proposed a procedure for evaluating the performance of public bus

operators' driving styles based on fuzzy logic [4]. The researchers utilized three parameters extracted from the velocity-acceleration diagram by defining membership functions, which identified the value for each parameter. Subsequently, a value of assessment index was obtained through an aggregation of the values above and assigned weights. Hongjie Ma et al. concentrated on the effects of acceleration behavior on fuel consumption among city buses [5]. Thirteen characteristic parameters were selected for an evaluation model adopting the method of decision tree C4.5, which could classify the drivers into several levels according to their energy economy. Moreover, there are also many patents on driving economy evaluations from automotive enterprises such as Toyota, King Long and Yamaha [6, 7, 8]. Specifically, they collect detection information from vehicle sensors and evaluate the driver's performance using manually set assessment parameters.

In consideration of existing approaches for drivers' economic efficiency assessments, the key challenges in this research are:

- The influence from road and vehicle conditions on the assessment result should be taken into consideration.
- The assigned weights and parameters of evaluation models must be objective.
- The assessment method should be applied to a variety of complex driving conditions, with the same effectiveness.

In this paper, a solution for an adaptable and objective assessment method is studied. On one hand, this study utilizes automotive theory to identify the influential factors of the driver operations on fuel consumption. The 12 selected characteristic indexes represent four aspects of driving behavior including speed, acceleration, engine and accessories control. Also, their effects are quantified based on a large amount of running data from more than 100 buses. Next, each index is evaluated using the threshold method and the results are combined with their respective weights to yield the driving pattern score. On the other hand, a statistical model is established to compute the ideal fuel consumption for specific maneuvers by applying the method of artificial neural network. Then, the fuel score is calculated using actual and ideal fuel consumption. Finally, the driving pattern score is validated and modified by comparing it to the fuel score.

DATA COLLECTION

Selection of Assessment Indexes

In order to establish a comprehensive evaluation model, several straightforward and definitive indexes are required. Marc Ross et al. constructed a model which showed the analytic relationship between fuel economy and driving conditions [9]. The model classified the fuel-related factors into six categories: engine friction, tire drag, air drag, braking, idling and accessories. Eva Ericsson collected data on nearly 20,000 driving patterns in real traffic situations [10]. Initially, 62 parameters were calculated but subsequently reduced to 16 using the method of factor analysis. These independent driving pattern factors covered the control strategies of velocity, acceleration and engine speed. Xiaohua Zhou et al. have also constructed a driving feature vector containing information on speed, vehicle specific power and acceleration [11]. The vectors indicate five distinct driving patterns, and their relationships with fuel consumption are revealed using a clustering algorithm.

In accordance with the aforementioned research, this study selects 12 driving pattern indexes including velocity, acceleration, engine state and accessories control, as shown in Table 1. The data is converted to an index per hundred kilometers to match the measurement of fuel consumption. Naturally these are all inverse indexes, which means the higher their values are, the lower their corresponding scores will be.

Data Collection for Assessment

A database of a fleet management system is adopted to collect the daily running data produced by a number of intercity buses operating on various routes. The vehicle traveling data recorder provides data collected through different types of sensors, while real-time tracking systems using Global Positioning System can locate the position of the vehicles wherever they are. By law, these devices are required to be installed in all operating vehicles. Thus, the running data including velocity, acceleration and position along the traveling path are

available for driving conditions and drivers' behavioral analyses. Using the collected data, the indexes shown in Table 1 are able to be calculated.

Table 1. Indexes selected to describe the driving pattern.

No	Index	Abbr.	Description	Unit
1	Speeding time	Time_exc	Time in speed > 100km/h	s/100km
2	Highest speed	Speed_hi	Average speed when speed > 100km/h (If speed always ≤ 100km/h, Speed_hi=0)	km/h
3	Speed fluctuation	Speed_std	Standard deviation of speed in interval 60-100km/h	km/h
4	% of time running in uneconomic state	%_uneco	% of time without engine speed 1000-1600r/min or load factor 40%-80%	%
5	Heavy acceleration frequency	Freq_acc	Count of heavy acceleration	/100km
6	Heavy acceleration time	Time_acc	Time of heavy acceleration	s/100km
7	Heavy deceleration frequency	Freq_dec	Count of heavy deceleration	/100km
8	Heavy deceleration time	Time_dec	Time of heavy deceleration	s/100km
9	Power-off coasting time	Time_neu	Time of power-off coasting	s/100km
10	Idling time	Time_idl	Time of idling for too long	s/100km
11	Over-speeding time	Time_over	Time of engine over-speeding	s/100km
12	Accessories time	Time_air	Time of using accessories including air conditioner and heater	s/100km

Furthermore, information about the route can be obtained by combining the GPS position with an online map database. The database outputs the locations and types of all infrastructures along the road according to the starting and ending latitude-longitude coordinates. The road condition information includes the number of traffic lights, road entrances and toll stations, all of which reflect the level of difficulty in driving to some extent. Thus, the evaluation result can be adjusted according to the difficulty classification.

This study involves 135 diesel buses of various models operating on complex routes in China, which are extracted from thousands of buses recorded by the fleet management system in consideration of data validity. In order to recognize different maneuvers, the characteristic parameters of each model are recorded, which contains the information of curb weight, passenger volume and engine displacement as well as its VIN. The running data are collected and measured by seconds.

METHODS OF DRIVING ECONOMY ASSESSMENT

Scoring Methods of Assessment Indexes

There are several common scoring methods to make the mentioned indexes dimensionless, thus allowing the different physical quantities to be comparable. The linear methods include the thresholding method, standardization method and relative proportion method. And the curve methods include exponential model and trigonometric method. For the indexes with similar magnitudes (Speed_hi, Speed_std and %_uneco), the thresholding method is used as follows:

$$y_i = a - \frac{bx_i}{S_i} \quad (i = 2, 3, 4) \quad (1)$$

where i is the number of index. x_i is the actual value of index i , and y_i is the assessing result of index i . Parameter S_i is the outstanding value of index i , which is obtained from the running data of excellent drivers with good fuel economy. In this study, the sample drivers are ranked according to their past records of fuel consumption, with the top 30% being regarded as the excellent drivers. The averages of their assessment indexes are set to be outstanding values. The parameters a and b are used to limit the value range of assessing results.

The remaining indexes are measured by applying the exponential model:

$$y_i = 100e^{-\frac{x_i}{cS_i}} \quad (2)$$

where the parameter c has the same function as a and b .

Notably, the driver's behavior is closely related to prevailing driving conditions. For instance, the driver must execute start-and-stop operations frequently when traveling in an urban area with many traffic lights. Thus, the idling time increases while the likelihood of heavy acceleration and deceleration becomes higher. For this reason, the driving pattern assessment should take driving environment into consideration. Although the impact of driving environment is difficult to quantify, this paper adopts a simple method by classifying the conditions into different difficulty levels.

To complete the classification, road parameters related to driving are required. V2X technology is a solution for collecting the information of surrounding traffic infrastructures and providing assistance for the driver [12, 13]. Specifically, it allows vehicles to communicate with traffic lights and road signs through wireless dynamic data exchange. Meanwhile, the traffic control center will transmit live traffic information to help select appropriate routes. The technology can be achieved through several devices including GPS, DSRC and mobile phones.

GPS is the most economical data access tool for commercial vehicles. The road information can be extracted from a digital map database by inputting the starting and ending latitude-longitude pairs. By querying the optimal traveling route, the numbers and positions of traffic lights, road entrances, landmarks, toll stations, gas stations and other infrastructures can be recorded. In this paper, the driving route is described with positions located by GPS per 100 seconds. The typical route parameters having the greatest influence on fuel consumption are the number of traffic lights, road entrances and toll stations per hundred kilometers. The difficulty level is quantified by the total number of the three parameters per unit of distance, which is named Number of Infrastructures per Hundred Kilometers (NIHK). The average of all sample maneuvers' NIHK is set to be Road Condition III. And the classification of road conditions is defined as shown in Table 2. The correction coefficient is set manually here, and it can also be derived from the historical data on specific drivers.

Table 2. Classification of road condition and corresponding coefficients

Road condition level	I	II	III	IV	V
NIHK	<0.4A ^a	0.4A-0.8A	0.8A-1.2A	1.2A-1.6A	>1.6A
Correction coefficient α	1.00	1.05	1.10	1.15	1.20

^a A is the average of all sample drivers' NIHK.

The driving pattern score can be obtained by combining the scores of all indexes. According to the correction coefficients, the driving pattern score is modified as follows:

$$y = \alpha \sum_{i=1}^{12} w_i y_i \quad (3)$$

where w_i is the weight of index i , which will be discussed in the next section.

MULTIPLE REGRESSION ANALYSIS AND DETERMINATION OF WEIGHTS FOR ASSESSMENT INDEXES

Another important part of the assessment model is the determination of weights for the assessment indexes. Multiple regression provides a solution for isolating and quantifying the unique effect of each driving behavior on fuel consumption. Regression analysis is a statistical procedure for estimating the relationship between a dependent variable and other independent variables. In consideration of the relationship type, this method can be distinguished between linear and nonlinear regression. In multiple linear regression, the model parameters indicate the impact degree of corresponding independent variables.