FEASIBILITY STUDY ON FUEL CONSUMPTION PREDICTION MODEL
BY INTEGRATING VSP AND CAN BUS TECHNOLOGY

by

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ABSTRACT

With the development of automobile technology, it becomes possible to estimate the fuel consumption using the driving parameters from the Electronic Control Unit (ECU) and output the calculation results via the Controller Area Network (CAN) bus. As a result, it is feasible to design an approach for estimating the fuel consumption by integrating vehicle specific power (VSP) and CAN bus technology because of the accessibility and stability of the CAN bus. In order to determine whether the CAN-based measured data can be used to build the relationship between VSP and fuel consumption to replace the traditional fuel consumption meter, a comparison of fuel consumption data collected from ECU and the fuel consumption meter is conducted in this study. The results show that the relationship between the fuel consumption rate and VSP bin built by the CAN bus data is consistent with the one derived from the fuel consumption meter, which indicates that the CAN bus technology can be used to describe the relationship between vehicle activities and fuel consumption rates for light-duty vehicles. In addition, a comparison of CAN-based measured data with VSP-based predicted data shows that the prediction approach that integrates VSP and CAN bus technology need an aggregation level of 60s or longer, which thus can be used to estimate a long-period of fuel consumption accumulation and fuel consumption factor for various travel speeds and road types.
INTRODUCTION
With the rapid social and economic development followed by the continued growth of automobile ownership, the road transportation has become a significant consumer of energy in modern cities. By May 2012, China’s foreign dependence ratio of oil was 56.7%, exceeding that of USA. By the end of 2011, the national motor vehicle population was over 220 millions, having increased with a high annual rate of 8.56% from 2010 to 2011 including 104 million light-duty vehicles. In addition, the automobile energy consumption in China is higher than that of the global average level, and the associated traffic congestion problem is becoming increasingly serious. For such a large, complex and rapidly growing road traffic system, the automobile energy conservation and emission reduction is a big challenge. Therefore, identifying a methodology for accurately calculating and evaluating the road traffic fuel consumption is an essential element in contributing to the solution of energy problems.

At present, the approach to estimate the fuel consumption at a micro-level falls into two categories. One is that the calculation is based on the experimental means. Direct measurements by fuel consumption meter and carbon balance method (1) are the widely used approaches at home and abroad. In the past few years, with the advancement of the modern automobile technology, the vehicle’s driving parameters can be readily obtained from the electronic control unit (ECU) via Controller Area Network (CAN). ECU is available for the calculation of the fuel consumption by providing driving parameters. CAN is a well-designed communications bus for sending and receiving short real-time control message at a speed of up to 1Mbit/sec (2). Developed in 1980s by Robert Bosch (3), its ease of use and low cost has led to its wide adoption throughout the automotive and automation industries. Thus, it has been possible to transmit the estimation result of fuel consumption to an external device based on the CAN bus technology.

Another method in estimation fuel consumption is through the fuel consumption prediction models. According to the theoretical basis of model development and the modeling method, the micro-level fuel consumption models can be divided into four types: (a) the model based on the analysis of engine power; (b) the model based on the decomposition of driving behavior; (c) the statistical model based on the speed-acceleration; and (d) the physical model based on the power demand. Because of the simple calculation process, the algorithm and modeling based on the relationship between Vehicle Specific Power (VSP) and fuel consumption has become the main trend for estimating the fuel consumption in recent years. Hence, the primary objective of this paper is to develop an efficient fuel estimation approach by integrating prediction models and the on-board technology for vehicle data collection.

LITERATURE REVIEW
Although the measurements by fuel consumption meter is able to provide the accurate data of fuel consumption, such method is still difficult to be widely used to evaluate the fuel efficiency in a large traffic network because of the high price of the facility and applicability
to various kinds of engines. For the experimental approach, the carbon balanced method is another choice to estimate the fuel consumption indirectly. However, this approach needs to measure each component’s mass of the vehicle emission, which is much difficult in the experiment. Fang et al. (4) compared the calculation result by the carbon balanced method with the data from the fuel consumption meter in China Automotive Technology & Research Center. The relative error was less than 2%, which satisfied the accuracy requirement. Nowadays, CAN bus technology could realize the function of information transmission from ECU to an external device. Zhong et al. (5) designed a CAN bus information conversion and output device to collect parameters for calculating the fuel consumption, such as engine speed. However, in the existing research, there is little work that focused on using the CAN bus measured data to build the prediction model for estimating the fuel consumption and evaluating its accuracy and applicability.

The model based on the analysis of engine power needs lots of input parameters with a complex calculating process. Models in this category include ADVISOR (6), PSAT (7) and EVSIM (8). For the model based on the decomposition of driving behavior, Akcelik et al. (9) divided the urban traffic into three driving modes and estimated the fuel consumption separately. In the further research, he added a driving mode and put them into SIDRA (10). For the third type of model, Andre et al. (11) and Joumard et al. (12) classified the speed and acceleration product, and then estimated the instantaneous fuel consumption by choosing the combination of speed and the product. The typical model of this method is MODEM. The model based on the power demand attempted to overcome the shortcomings of the statistical method, which is that it cannot explain the principle of vehicle emissions. Such models include CMEM (13) and MOVES (14). As the representative model, MOVES (MOtor Vehicle Emission Simulator) is Environmental Protection Agency (EPA)’s current official model for estimating emissions and fuel consumption from cars, trucks and motorcycles. This new emission modeling system estimates emissions and fuel consumption for mobile sources covering a broad range of pollutants and allows multiple scale analysis. In addition, Nam (15) developed PERE model for MOVES to represent the latest progress of the modeling work for the micro-level fuel consumption and emission methodology.

Based on the above review of existing fuel consumption models, no study has been found that analyzed the prediction model by integrating VSP and the CAN bus technology. With the development of the modern automobile technology, it is possible to design an approach based on the CAN bus technology that can replace the traditional fuel consumption meter to establish the relationship between vehicle activities and the fuel consumption because of the accessibility and stability of CAN bus.

This paper is intended to study the feasibility of integrating the VSP and CAN bus technology to predict the fuel consumption in order to replace the traditional fuel consumption meter. To this end, the predicted data by using the model based on the relationship between VSP and the fuel consumption rate is compared with the measured data by CAN-bus technology in order to determine the feasibility of the VSP-based prediction model.
METHODOLOGY

Source of Data
In this study, a gasoline-fueled Nissan Altima installed with a Snap-on Microscan OBD-II Scanner to collect ECU data via CAN bus and a global position system (GPS) was used to collect two types of field data.

The first type is the driving parameters collected through ECU. It collects the vehicle’s driving parameters such as the engine RPM, the intake manifold absolute pressure and the intake air temperature, and then calculates the fuel consumption by the methodology introduced in next section. After that, ECU outputs the second-by-second fuel consumption rate data via CAN bus in the unit of µl/s.

The second type of data is the GPS data. The Columbus V-900 Multifunction GPS Data Logger is used in the test. The raw data consist of time, geographic information and instantaneous speed on a second-by-second basis. The second-by-second acceleration is calculated by the instantaneous speed using Equation (1):

\[ a_n = v_n - v_{n-1} \]  

where

- \( a_n \) = the acceleration of the \( n^{th} \) second in the unit of m/s\(^2\),
- \( v_n \) = the instantaneous speed of the \( n^{th} \) second in the unit of m/s.

The 2007-model-year Altima’s engine displacement is 2.5L, and its odometer shows 70,000km. In order to collect data from a wide-variety of traffic conditions, the vehicle was tested in the pre-designed routes in Beijing, China that covered diverse vehicle operating conditions and the various road types, as shown in FIGURE 1. Each test lasted about four hours including two peak hours and two non-peak hours for two days in July 2012. These field data via CAN bus and GPS are used to build the relationship between fuel consumption and vehicle activities for developing the prediction model in this study.

![FIGURE 1 Pre-designed test routes](image_url)
second-by-second data are identified for this study. Each pre-processed record includes time, road name, travel speed and the flow consumption rate calculated from ECU via CAN bus. The survey details and sample pre-processed records are listed in TABLE 1.

### TABLE 1 Survey Details and Sample Pre-processed Records

<table>
<thead>
<tr>
<th>Date</th>
<th>Starting Time</th>
<th>End Time</th>
<th>Total Record</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012.7.12_peak hours</td>
<td>07:22:28</td>
<td>09:24:45</td>
<td>6,393</td>
</tr>
<tr>
<td>2012.7.12_non-peak hours</td>
<td>09:41:55</td>
<td>11:32:50</td>
<td>6,609</td>
</tr>
<tr>
<td>2012.7.13_peak hours</td>
<td>07:25:09</td>
<td>08:48:36</td>
<td>4,941</td>
</tr>
<tr>
<td>2012.7.13_non-peak hours</td>
<td>09:34:02</td>
<td>11:02:49</td>
<td>5,265</td>
</tr>
</tbody>
</table>

### ID | Date | Time       | Road name      | Speed(km/h) | Flow Rate(μl/s) |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1008</td>
<td>7.12</td>
<td>09:58:47</td>
<td>Zizhuyuan Rd.</td>
<td>30.2</td>
<td>3,710</td>
</tr>
</tbody>
</table>

### Calculation Method by ECU

The process is to calculate the mass air flow (MAF) through driving parameters from ECU via CAN bus first (16), and then figure out the fuel flow. Further, the fuel consumption will be estimated from the fuel flow and vehicle speed. It should be noted that the data obtained by ECU is a binary number, which needs to be converted into a decimal number.

#### Calculation Method of MAF

There are three methods available for calculating the MAF through various parameters.

- If SAE.MAF (SAE, a standard published by the Society of Automobile Engineers, which provided industry references for measurement of engine power) from ECU is available, MAF can be calculated using Equation (2):

  \[
  MAF = \frac{(256 \times A + B)}{100}
  \]  

  \[\text{(2)}\]

  where

  \[A, B = \text{return binary value of SAE.MAF from ECU.}\]

- If SAE.LOAD_ABS (the absolute load value) is available, MAF can be calculated using Equation (3):

  \[
  MAF = \frac{\text{air} \_ \text{density} \times \text{displacement} \times \text{load} \_ \text{abs} \times \text{engine} \_ \text{speed}}{120[\text{min/ r}]} \]

  \[\text{(3)}\]

  where

  \[\text{air} \_ \text{density} = \text{the density of air in the unit of g/l, generally take 1.184g/l,}\]

  \[\text{displacement} = \text{the displacement of engine in the unit of l,}\]

  \[\text{load} \_ \text{abs} = \text{the absolute load value in the unit of %, and}\]

  \[\text{engine} \_ \text{speed} = \text{the speed of engine in the unit of r/min.}\]

- If manifold absolute pressure (MAP) and intake air temperature (IAT) are available, MAF can be calculated using Equation (4):

  \[
  MAF = \frac{(\text{MAP} \times \text{IAT}) \times (M \times R) \times (\text{RPM} \times 60) \times (\text{ED} \times 2) \times \text{VE}}{\text{VE}}
  \]  

  \[\text{(4)}\]

  where

  \[\text{MAP} = \text{the intake manifold absolute pressure in the unit of kPa,}\]
Fuel flow can be calculated from MAF using Equations (5) and (6):

\[
\text{Fuel flow} [l/h] = \text{MAF} / (\text{AFR}_{\text{actual}} \times \text{fuel \_ density})
\]

(5)

\[
\text{AFR}_{\text{actual}} = \lambda \times \text{AFR}_{\text{optimal}}
\]

(6)

where

- \( \text{AFR}_{\text{actual}} \) = the actual air-fuel ratio,
- \( \text{AFR}_{\text{optimal}} \) = the optimal air-fuel ratio, generally take 14.64 for gasoline,
- \( \lambda \) = a parameter from ECU provided by Universal Exhausts Gas Oxygen Sensor, and
- \( \text{fuel \_ density} \) = the fuel density in the unit of g/ml.

If the fuel is diesel, it needs the load value calculated from ECU to modify the Equation (5) by multiplying the load value (SAE.LOAD_PCT) in the unit of %.

The calculation of instantaneous fuel consumption \( (IFC) \) is based on

\[
IFC = \text{Fuel \_ flow} / \text{SAE.VSS}
\]

(7)

where

- \( \text{SAE.VSS} \) = the vehicle speed from ECU in the unit of km/h.

The calculation of average fuel consumption \( (AFC) \) is based on

\[
AFC = \frac{\text{Fuel}_T}{d_T}
\]

(8)

where

- \( \text{Fuel}_T \) = the total fuel consumption in the certain period \( T \), and
- \( d_T \) = the total travelled distance in the certain period \( T \).

The entire calculation process is shown in \textbf{FIGURE 2}.
In order to calculate the fuel consumption of light-duty vehicle by the prediction model, it is necessary to derive traffic characteristics that can directly represent the level of fuel consumption. For this purpose, the relationship between the fuel consumption based on CAN bus technology and vehicle activities is first established, in which the VSP-based approach is adopted. Then, to verify that the CAN data can be used for the model development, a comparison of fuel consumption data collected by ECU and the fuel consumption meter is conducted to determine the relationship between normalized fuel consumption and VSP bin distribution.

**Relationship between Fuel Consumption and Vehicle Activities**

The parameter of VSP is utilized in analyzing the relationship between fuel consumption and vehicle activities. VSP (kW/ton) is defined as the instantaneous tractive power per unit vehicle mass. For a typical light duty vehicle, VSP can be calculated using Equation (9) \((17, 18)\):
\[ VSP = v \cdot [1.1a + 9.81 \cdot \text{grade}(\%) + 0.132] + 0.000302v^3 \]  

(9)

where:

\[ v = \text{vehicle speed in the unit of m/s}, \]

\[ a = \text{vehicle acceleration in the unit of m/s}^2, \]

\[ \text{grade}(\%) = \text{vehicle vertical rise divided by the slope length}. \]

The road grade is assumed to be zero in this research, so the VSP equation can be simplified as:

\[ VSP = v \cdot [1.1a + 0.132] + 0.000302v^3 \]  

(10)

In the analysis, the binning approach is applied to avoid the random errors that could appear from the second-by-second fuel consumption meter data, in which the VSP data are binned into 1kW/ton (19), as shown in Equation (11), and then the average fuel consumption rate within each bin is calculated.

\[ \forall : VSP \in [n - 1, n), VSP \text{ Bin} = n \]  

(11)

In the urban traffic network, almost all the data fall into the VSP interval of -25 to 25kW/ton (20). So, the rest of the analysis is conducted for this interval. In this study, the fuel consumption data calculated by ECU via CAN is used to build the relationship between VSP and fuel consumption rate instead of using the traditional approach that obtained the fuel rate data from a fuel consumption meter. FIGURE 3 illustrates the average fuel rate calculated by ECU and the data frequency in each VSP bin.

**FIGURE 3 Average fuel rate and data frequency in each VSP bin**

Fuel rates show two distinct trends in positive and negative sides of VSP. They increase monotonically with VSP in the positive side, while remain almost constant at low values in the negative VSP side. From Equation (10), it can be derived that all the negative VSP values are corresponded with the deceleration modes of vehicles, so the above trends are physically explainable. In addition, the trends are similar to those for the light-duty vehicles which were collected from the fuel consumption meter in existing studies (19) (20).
Relationship between Normalized Fuel Consumption and VSP Bin Distribution

For the purpose of further evaluating whether the fuel consumption rate calculated by ECU can be used to build the relationship between VSP and the fuel consumption, a comparison of fuel consumption data collected from ECU and fuel consumption meter is conducted. The change of fuel consumption with VSP is used to evaluate the difference between the fuel consumption derived from the two approaches.

The fuel consumption data collected from three automobile models, Jetta, Fukang and Sonata by a fuel consumption meter Flowtronic Sensor S8005C are used to form a control group. However, it is noted engine size, fuel type, and vehicle mass have considerable effects on the absolute fuel consumption rates (21). In order to eliminate these effects and reflect the relative changes of fuel consumption with VSP, Song et al. (19) designed a normalization approach, termed as “normalized fuel rate (NFR),” in which, the average fuel rates are divided by its idling rate (in VSP bin of 0).

With this approach, the regression analysis is carried out for each data group, as shown in FIGURE 4. For the test vehicles, the power regression model \( y=ax^b \) is determined to be appropriate in representing the variations of NFR within positive VSP bins, in which the determination coefficients of the regressions are all higher than 0.95. The average \( a \) of the regression model in the control group is 1.704, while it is 1.729 when using the CAN bus measured data with a relative error of 1%. The average \( b \) in the control group is 0.384, while it is 0.360 in the test group with a relative error of 6%. In the negative VSP side, all the NFRs remain almost constant, which are nearly equal to 1. The average NFRs in negative VSP bins for Jetta, Fukang, and Sonata are 1.00, 1.04, and 1.05 respectively. For the CAN bus measured data, the average NFRs is 0.95 with a relative error of 7%.

It still should be noted that the consistency of NFRs in FIGURE 4 may be attributed to the similarities in the engine maps and more broadly similarities in vehicles and technologies, which needs further investigations with broader vehicle types and technologies.

Based on the above analysis, it is assumed that the NFRs of the light duty vehicles follow the same variation rule as what was presented above. Hence, the fuel consumption rate data calculated by ECU via CAN bus can be used to describe the relationship between vehicle activities and fuel consumption rates for light-duty vehicles.
Calculation Method of Fuel Consumption Factor

The fuel consumption can now be estimated by the relationship between VSP and fuel consumption, as shown in FIGURE 4. In order to compare the predicted result with the fuel consumption calculated by ECU via CAN, the fuel consumption factor \( FCF \) in each speed level is designed as an index, as shown in Equation (12).

\[
FCF = 3600 \cdot \sum_{\nu} \frac{\text{fuel consumption}}{\nu} \tag{12}
\]

where \( FCF \) is the fuel consumption factor in the unit of g/km, \( \text{fuel consumption} \) is estimated by the relationship for each speed level in the unit of g/s, and \( \nu \) is the average travel speed in the unit of km/h.
EVALUATION OF THE PREDICTION MODEL

For evaluating the VSP-based prediction model, this section analyzes and compares the calculation results from CAN-based approach and those from VSP-based prediction model. The comparison is conducted from perspectives of short-period average fuel rate, the total fuel consumption, fuel consumption in different road types and fuel consumption in different travel speeds.

Evaluation of the Model on Fuel Rate and the Total Fuel Consumption

The comparison of different short-period average fuel rates is shown in FIGURE 5, where the aggregation level is 10s, 30s, 60s and 120s respectively. The process of the aggregation is to bin the data in a specific interval (such as 10s) together, then calculate the average value in each interval. To evaluate the prediction model, many indexes can be used. Hanna (22) used NMSE (Normalized Mean Square Error) to evaluate the average relative discrete degree, which is adopted in evaluating CHEM (13), as shown in Equation (13).

\[ NMSE = \frac{\sum_{i} (C_o - C_p)^2}{n \cdot C_o \cdot C_p} \]  (13)

where \( C_o \) is the CAN-based measured value and the \( C_p \) is the VSP-based predicted value.
(a) Average fuel rate in the aggregation level of 10s

(b) Average fuel rate in the aggregation level of 30s

(c) Average fuel rate in the aggregation level of 60s

(d) Average fuel rate in the aggregation level of 120s

FIGURE 5 Comparison of different short-period average fuel rates
In an accurate model, the $NMSE$ should be close to 0. Song (20) in his doctoral dissertation proposed that $NMSE<0.5$ is the acceptable limit. For the calculation results, the $NMSE$ in each aggregation level of 10s, 30s, 60s and 120s is 0.966, 0.636, 0.463, and 0.361. The results show the method needs a no less than 60s aggregation level to estimate the fuel consumption, because the short-period prediction can not reflect the CAN-based measured fuel consumption level.

The total fuel consumptions of the two methods are very close with relative errors of 6.12%, 5.22%, 1.14% and 4.53% in each period, as shown in FIGURE 6. It shows that the VSP-based prediction model is rather accurate in calculating the total fuel consumption for the light-duty vehicle. It should be noted that the similarity between peak and non-peak hours is attributed to the insufficient testing time and the total record number. In the field test, it really cannot tell the difference of the fuel consumption in the peak hour from that in the non-peak hour which needs further studies in the future.

![FIGURE 6 Total fuel consumption in each period](image)

From the above analysis, the prediction approach by integrating the VSP and CAN bus technology requires 60s or higher aggregation level, which can then be used to estimate a long-period fuel consumption accumulation. However, it is not suitable for the prediction of short-period fuel consumption because the using of the average fuel consumption rates in the VSP bins smoothes the instantaneous variation of fuel consumption.

**Evaluation of the Model on Fuel Consumption for Different Travel Speeds**

$FCF$ in each speed level is adopted for the evaluation of the prediction model, because the speed is an important factor that influences the fuel consumption for light-duty vehicles.

The comparison result of $FCF$ in each speed bin is shown in FIGURE 7. The $FCF$s of two methods are consistent with the variation trend of the average speed. It indicates that the prediction value is able to reflect the real-world change of $FCF$, which shows the descending trend from the low speed to high speed. In addition, the relative error in the low speed interval is apparently lower than that in the high speed because of the longer testing
time and larger records in the low speed interval. In the above analysis, the prediction approach could perform better in a long period travel, so the prediction result in the low speed interval is closer to the measured data calculated by ECU than that in the high speed interval. It shows that the prediction approach based on the VSP bins requires a large amount of measured data in order to build an accurate model. Insufficient data cannot represent the real relationship between VSP and the fuel consumption.

**FIGURE 7** Comparison of FCF in different travel speed

**Evaluation of the Model on Fuel Consumption Factor for Different Road Types**

In the test, the pre-designed route covered various road types including expressways, principal arterials, minor arterials and local streets. The FCF is used to evaluate the prediction model for different road type, as shown in **FIGURE 8**.

It is shown that the trend of each road type is consistent with the variation trend of the average speed. In the low speed interval, the slope is larger than that in the high speed interval. For each road type, the trend of the predicted FCF based VSP bin distribution is very close to that of the CAN bus-based output FCF. In arterial roads, the relative error is smaller than that of other two road types, because most of the measured data are collected from the arterial roads. In the minor arterials and local streets, the travel speed is lower than that of other two road types because of the different traffic conditions on different road types. Further, the FCF is higher in the low grade road than that in other two road types.
FIGURE 8 Comparison of $FCF$ for different road types
In the test, a great quantity of data could not be collected for each road type because of the limitation of the CAN bus protocol for a specific vehicle, so there observed no significant difference between road types. In the future, more field data calculated by ECU via CAN will be used to analyze the difference between road types.

CONCLUSIONS

Based on the evaluation of the data provided by ECU via CAN bus and the data derived from the prediction model by integrating VSP and CAN data, it shows that the second-by-second fuel rate data collected by CAN bus technology can reflect the relationship between vehicle activities and fuel consumption for the light-duty vehicle. Therefore, the modeling using CAN data is feasible for calculating the vehicle fuel consumption. The main findings in this study can be summarized as follows:

1. Fuel consumption rates calculated by ECU via CAN bus show distinct trends in positive and negative sides of VSP bins. They increase monotonically with VSP in the positive side, while remain almost constant at low values in the negative VSP side. From Equation (10), it can be derived that all the negative VSP values are corresponded with the deceleration modes of vehicles, so the above trends are physically explainable.

2. The normalization of fuel consumption can avoid having to address the effect of engine size and vehicle mass on the absolute fuel consumptions. Through the comparison between CAN-based data and the fuel consumption meter data of Jetta, Fukang and Sonata, the fuel consumption rate data calculated by ECU via CAN bus can replace the data collected by the fuel consumption meter to be used for developing the VSP-based prediction model.

3. In order to evaluate the modeling based on the CAN bus data, the fuel consumption rate in different aggregation levels and the total fuel consumptions are used to evaluate the consistency of the data from the prediction model and the CAN bus. The result showed that the prediction model based on the VSP bin can be used to estimate fuel consumption accumulation a period of time after an aggregation of 60s or higher period. However, it is not suitable for the prediction of short-term fuel consumption because the using of the average fuel consumption rates in the VSP bins smoothes the instantaneous variation of fuel consumption. Further, the fuel consumptions for different travel speeds and road types are also compared. The results show that average FCFs for different travel speeds and road types are consistent with the variation trend of the average travel speed.

There are some limitations of this study that would need further improvements. First, the CAN bus technology is secrecy for each automobile company, thus the test could not collect a large quantity of field data for various vehicle types and CAN bus technologies. Second, the fuel consumption meter should be used to collect the second-by-second fuel consumption rate data for the comparison with the data calculated by ECU. Third, more field data are needed for different road types and time periods in order to compare different relationships between the fuel consumption and travel speed in peak vs. non-peak hours and for various road types.
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