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# Modeling and Verification of Eco-Driving Evaluation

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**Abstract**
Traditional ecological driving (Eco-Driving) evaluations often rely on mathematical models that predominantly offer subjective insights, which limits their application in real-world scenarios. This study develops a robust, data-driven Eco-Driving evaluation model by integrating dynamic and distributed multi-source data, including vehicle performance, road conditions, and the driving environment. The model employs a combination weighting method alongside K-means clustering to facilitate a nuanced comparative analysis of Eco-Driving behaviors across vehicles with identical energy consumption profiles. Extensive data validation confirms that the proposed model is capable of assessing Eco-Driving practices across diverse vehicles, roads, and environmental conditions, thereby ensuring more objective, comprehensive, and equitable results.

**Keywords**
Combination Weighting Method, Data-Driven, Eco-Driving, K-Means Clustering

## 1. Introduction

Evaluations of ecological driving (Eco-Driving) typically analyze the fuel or power consumption produced by vehicles over a specific driving distance. The methods for evaluating vehicle energy consumption are summarized through an analysis of the vehicle energy consumption under various driving behaviors [1] and the correlation between driving behaviors and vehicle energy consumption [2,3]. Lee and Jung [4] considered the traffic conditions of the host vehicle and its surrounding environment when establishing Eco-Driving evaluation system. In [5], certain environmental factors, such as vehicles, pedestrians, and animals, were integrated into the design of the driving simulator to facilitate simulation experiments of Eco-Driving system. The aforementioned methods focused solely on investigating the effect of driving behaviors on energy consumption within a single-vehicle closed scenario. However, the research regarding multi-vehicle and diverse environmental conditions is not sufficiently comprehensive. Examining the effect of a multi-driving environment and various driving behaviors on vehicle energy consumption using the aforementioned methods can be challenging. Furthermore, Zhang and Jin [6] and So et al. [7] focused on analyzing the vehicle trajectory. They proposed algorithms and control strategies to address the issue of Eco-Driving by examining the vehicle speed and torque curve. Internet of Vehicle (IoV) technology leverages mobile edge computation and path planning algorithms to accomplish distributed computing tasks [8,9], thereby efficiently decreasing


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fuel consumption and enhancing vehicle safety.

Based on Ma and Wang [10], a fuel-efficient driving strategy was introduced to minimize trip accumulated fuel consumption, taking into account the diversity of driver behaviors. However, comprehending the concept of Eco-Driving poses challenges for drivers, potentially leading to an increased burden on driving tasks. Therefore, Eco-Driving system must detect driving behaviors that consume energy and offer drivers real-time evaluations of their driving behavior along with relevant driving recommendations. This paper presents a data-driven Eco-Driving evaluation model that relies on various sources of information, including vehicle performance and driving environment, facilitated by IoVs. The model indirectly facilitates the evaluation of Eco-Driving performance among drivers in diverse scenarios involving multiple vehicles, roads, and environmental conditions. Furthermore, it encourages the development of an Eco-Driving system in subsequent stages.

The subsequent sections of this paper are structured as follows: Section 2 introduces the ecological evaluation model. In Section 3, the model is simulated and verified. Section 4 provides a summary of the paper's content and draws conclusions.

## 2. Model Establishment

The variations in energy consumption among different vehicle models and driving environments can be attributed to the diverse vehicle performance and driving scenarios. Assessing the driver's Eco-Driving performance under various conditions involving multiple vehicles, roads, and environmental factors poses a significant challenge. Vehicular ad-hoc network (VANET) facilitates the exchange of information between vehicles and their surrounding environment [11,12], thereby offering technical support for data collection. This paper primarily examines the energy consumption of vehicles with same characteristic energy consumption levels and assesses the practice of Eco-Driving by drivers. The model process is depicted in Fig. 1. Vehicles with same energy consumption characteristics take into account the key factors that primarily effect the energy consumption of the vehicle, resulting in same energy consumption patterns under corresponding driving conditions.

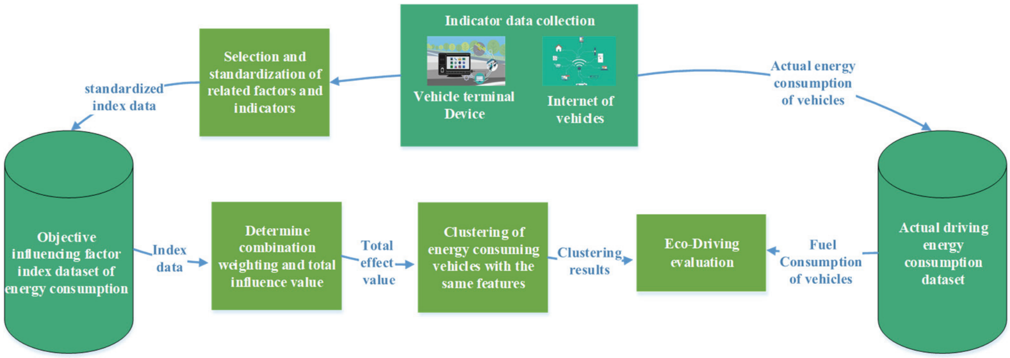


**Fig. 1.** The process of the Eco-Driving evaluation model.

The evaluation model should quantify the effect of various vehicle performance metrics and driving conditions on energy consumption. Subsequently, vehicles with equivalent energy consumption will be categorized based on their effect. It is essential to contemplate the selection and articulation of factors that affect vehicle energy consumption.

Firstly, this section identifies the indices of factors that affect energy consumption. Secondly, the normalization of indexes is conducted to mitigate the effect of dimension and variation range on the calculation of the overall effect value. Thirdly, by integrating the normalized values of individual factors, it becomes feasible to ascertain the comprehensive effect value of the primary objective factors on vehicle energy consumption. Finally, cluster analysis was employed to group vehicles sharing same characteristics related to energy consumption. The quantification of the variance in real energy consumption among vehicles possessing identical characteristics was conducted to assess drivers' Eco-Driving practices.

## 2.1 Index Selection and Standardized Treatment

### 2.1.1 Factor index selection

Various factors effect the energy consumption of vehicles during driving, encompassing both subjective and objective elements. These factors include road conditions, traffic conditions, traffic management strategies, the driver's physical and mental state, and driving speed. According to the research focus of this paper, four primary factors have been chosen to delineate the effect of objective variables on vehicle energy consumption: vehicle performance, road conditions, traffic conditions, and meteorological conditions.

### 2.1.2 Factor index standardization

The data on objective factors is standardized subsequent to the collection of the dataset comprising pertinent indicators of objective factors from various vehicles and driving environments. The significance of the data is directly related to the effect of the relevant objective factors on energy consumption. Vehicle performance is assessed based on the official theoretical fuel consumption $TF_S$. The road condition $RC_S$ is evaluated based on the combined effect of the flatness index and slope [13]. The relative speed ratio $RS_S$ serves as the evaluation metric for traffic conditions, primarily characterizing road capacity. $I_S$ represents the numerical value of the road meteorological environment index.

In summary, the corresponding indexes and symbols are outlined in Table 1.

**Table 1.** Factors affecting energy consumption and related symbols

| Level | Affecting factor | Relevant index | Normalized symbol |
|---|---|---|---|
| Vehicle | Vehicle performance | Theoretical energy consumption | $TF_S$ |
| Road | Road condition | Flatness index and slope | $RC_S$ |
| Environment | Traffic environment | Relative speed ratio | $RS_S$ |
| | Road environment meteorology | Total meteorological factors | $I_S$ |

## 2.2 Combined Weighting

Following data processing, Eco-Driving situations of the drivers were assessed using the combination weighting method [14] as outlined in the evaluation model proposed in this study. The verification of the evaluation model and data processing is implemented through MATLAB programming. The combination weighting method employs analytic hierarchy process (AHP) and entropy weight method to calculate the weights of four objective factors. Subsequently, the least squares method is employed to amalgamate and enhance the weight coefficients of the four primary objective factors. The weights of vehicle performance, road condition, traffic environment, and road meteorological environment, determined by AHP and entropy weight method, combining consistency tests and normalized weights, are established as $U = [u_1, u_2, u_3, u_4]$ and $V = [v_1, v_2, v_3, v_4]$. After optimization, the composite weight value can be represented as $W = [w_1, w_2, w_3, w_4]$. The effectiveness of the effect is enhanced when there is minimal variance between the total effect values calculated through subjective and objective weighting methods. Assuming there are n data acquisitions, the optimization model for combining objective and subjective weights using the least squares method can be defined as follows:

$$minH(w) = \sum_{i=1}^{n}\sum_{j=1}^{4}\left\{\left[\left(u_j - w_j\right)r_{ij}\right]^2 + \left[\left(v_j - w_j\right)r_{ij}\right]^2\right\}, \tag{1}$$

where $\sum_{j=1}^{4} w_j = 1$. When solving the optimization model that combines subjective and objective weights using the least squares method, the Lagrange function of the model is derived as follows:

$$L = \sum_{i=1}^{n}\sum_{j=1}^{4}\left\{\left[\left(u_j - w_j\right)r_{ij}\right]^2 + \left[\left(u_j - w_j\right)r_{ij}\right]^2\right\} + \lambda\left(\sum_{j=1}^{4} w_j - 1\right). \tag{2}$$

The equations presented can be derived by taking the derivative of Lagrange function associated with the model.

$$\frac{\partial L}{\partial w_j} = -\sum_{i=1}^{n} 2\left(u_j + v_j - 2w_j\right){r_{ij}}^2 + \lambda, \tag{3}$$

$$\frac{\partial L}{\partial \lambda} = \sum_{j=1}^{4} w_j - 1 = 0. \tag{4}$$

Eq. (3) and (4) can be expressed by a matrix as follows:

$$\begin{pmatrix} A & E \\ E^T & 0 \end{pmatrix} \cdot \begin{pmatrix} W \\ \frac{1}{4}\lambda \end{pmatrix} = \begin{pmatrix} B \\ 1 \end{pmatrix}, \tag{5}$$

where $A_{4\times4} = dig(\sum_{i=1}^{n} {r_{i1}}^2, \sum_{i=1}^{n} {r_{i2}}^2, \sum_{i=1}^{n} {r_{i3}}^2, \sum_{i=1}^{n} {r_{i4}}^2)$, $E_{4\times1} = [1,1,1,1]^T$, $W_{4\times1} = \left[w_1, w_2, w_3, w_4\right]^T$, $B_{4\times1} = \left[\sum_{i=1}^{n}\frac{1}{2}(u_1 + v_1){r_{i1}}^2, \sum_{i=1}^{n}\frac{1}{2}(u_2 + v_2){r_{i2}}^2, \ldots, \sum_{i=1}^{n}\frac{1}{2}(u_4 + v_4){r_{i4}}^2,\right]$. The weight value of the combination of four main objective factors after optimization can be obtained through Eq. (5) as follows:

$$W = A^{-1} \cdot \left[B + \frac{1 - E^T A^{-1} B}{E^T A^{-1} E} \cdot E\right]. \tag{6}$$

## 2.3 Cluster Analysis

This paper uses K-means clustering [15] to investigate scenarios where the objective factors exhibit identical characteristics in relation to vehicle energy consumption. The genetic algorithm utilizes a fitness function created through global approximation of the minimum sum of squared errors (SSE) associated with each $K$ value to optimize the clustering center. When optimizing the cluster center, the calculation equation for SSE is defined as follows:

$$SSE = \sum_{z=1}^{k}\sum_{X \in C_z} dist(U_z - X)^2, \tag{7}$$

$$U_Z = \frac{\sum_{X \in C_Z} X}{h_z}, \tag{8}$$

where $U_z$ is the $z$-th cluster center of energy-consuming vehicles with the same characteristics; $C_z$ is the $z$-th cluster of energy-consuming vehicles with the same characteristics; and $h_z$ is the total number of collected data for energy-consuming vehicles with the same characteristics in the $z$-th cluster $C_z$, respectively.

To calculate the total effect value of objective factors for 20,000 sets of data, K-means clustering, K-means++ clustering, and K-means clustering optimized by a genetic algorithm were employed to assess the SSE for the respective *K* values. The obtained from SSE analysis data are presented in Table 2.

Table 2 illustrates that SSE of K-means clustering significantly decreases after optimizing the initial clustering center using the genetic algorithm, resulting in improved clustering effectiveness. For the specific *K* value identified through the aforementioned three K-means clustering iterations, the variation in SSE data is illustrated in Fig. 2.

**Table 2.** SSE of K-means clustering under corresponding K value

| Cluster *K* | K-means | K-means++ | Optimized K-means |
|---|---|---|---|
| 2 | 103.782 | 103.781 | 104.280 |
| 3 | 52.792 | 53.193 | 52.710 |
| 4 | 31.496 | 31.253 | 31.288 |
| 5 | 20.769 | 20.857 | 20.465 |
| 6 | 15.554 | 15.491 | 15.089 |
| 7 | 11.955 | 11.828 | 11.101 |
| 8 | 10.541 | 9.678 | 8.627 |
| 9 | 7.387 | 7.753 | 7.057 |
| 10 | 6.606 | 6.039 | 5.608 |

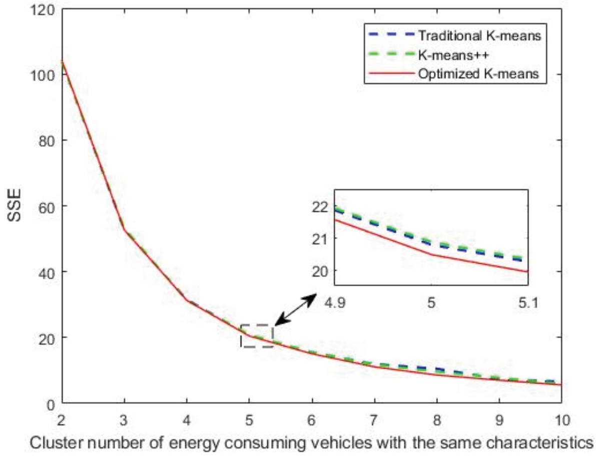


**Fig. 2.** Variation in SSE for K-means clustering under at various *K* values.

When $K = 5$ is selected as the number for clusters of vehicles with the same characteristic energy consumption, the K-means clustering benefit is optimal. The number of vehicles with the same characteristic energy consumption in each cluster is shown in Fig. 3.

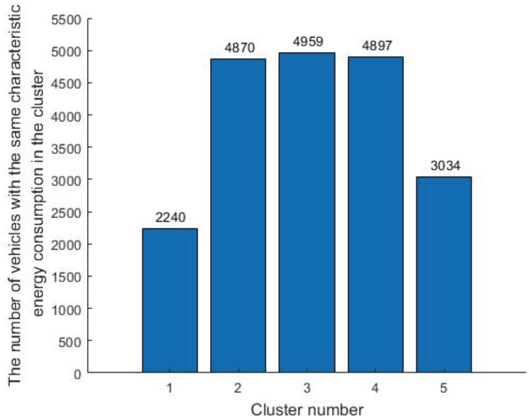


**Fig. 3.** Distribution of vehicles with the vehicle clusters based on same characteristic energy consumption characteristics.

## 2.4 Eco-Driving Evaluation Model

This paper presents the conversion of the collected data into fuel consumption for a vehicle traveling 100 km, measured in L/100 km. The evaluation model is defined as follows:

$$FCEV_i = 1 - \frac{AF_i - \min(AF)}{\max(AF) - \min(AF)}, \tag{9}$$

where $FCEV_i$ is the evaluation value; $AF_i$ is the actual driving energy consumption; and $AF$ is the actual driving energy consumption data set of all vehicles collected in the cluster of vehicles, respectively. A higher evaluation value of $FCEV_i$ indicates a more energy-efficient driving condition.

Eco-Driving behavior of the driver among vehicles is evaluated with identical characteristic energy consumption as defined in Eq. (9). The distribution histogram illustrating Eco-Driving evaluation values of drivers in the five clusters of vehicles is depicted in Fig. 4.

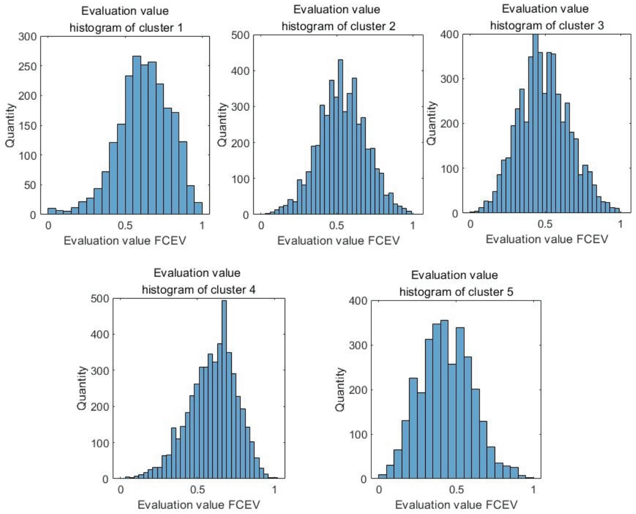


**Fig. 4.** Eco-Driving evaluation for clustered groups of vehicles based on same energy consumption characteristics.

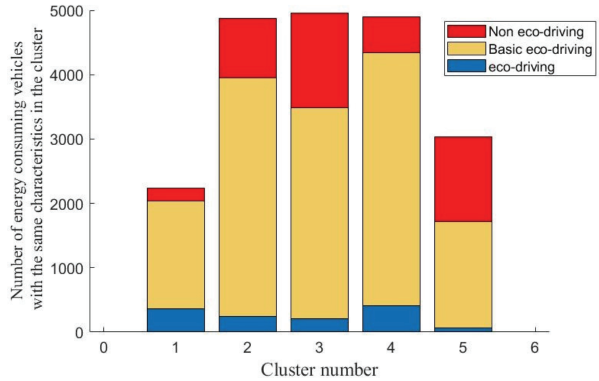


**Fig. 5.** Division of Eco-Driving performance among drivers in homogeneous energy consumption vehicle clusters.

When establishing the appropriate threshold, it is possible to segment Eco-Driving evaluation value of the respective driver from the vehicle cluster with same energy consumption characteristics. It is categorized into three groups: non-Eco-Driving ($FCEV \leq 0.4$), basic Eco-Driving ($0.4 < FCEV < 0.8$), and Eco-Driving ($FCEV \geq 0.8$). Within the cohort of 20,000 driver groups exhibiting same energy consumption patterns, Fig. 5 illustrates the distribution of Eco-Driving practices among the drivers.

# 3. Model Simulation and Verification

The efficacy of the driver's Eco-Driving evaluation model is substantiated through simulation-based verification. Given the necessity for a comprehensive database to support the evaluation model, this section delineates the construction of a database encompassing all requisite indicators of objective factors. Subsequently, the proposed Eco-Driving evaluation model is verified using this systematically assembled database.

## 3.1 Construction of Index Database

Based on the data requirements outlined in the evaluation model presented in this study, various components such as the vehicle terminal, on-board diagnostics (OBD), oil level sensor, camera, and other relevant equipment are utilized for the collection of actual index data. This data is essential for the development of a diverse database encompassing objective factors. This study compiles pertinent data from vehicle sales websites, verifies compliance with national industry standards, and integrates information from terminal devices to establish a comprehensive database encompassing multiple vehicles, roads, and environments.

In the simulation verification of this model, the sedan vehicle is exclusively considered as the subject of research, and a database of pertinent indicators of primary objective factors is established for the sedan vehicle. In regard to determining the actual driving energy consumption of the vehicle. Initially, the actual energy consumption of the vehicle is determined by utilizing the four objective factors gathered and analyzed by the vehicle terminal device. Subsequently, a sequence of arbitrary numerical values is introduced to depict the alteration in driver behavior for the purpose of estimating the real driving energy usage. Ultimately, the final energy consumption value for the respective vehicle's driving is ascertained.

This study examines the data requirements for comprehensive database by analyzing the construction method of database-related index data. It also explores the relationship between objective factors influencing vehicle energy consumption and actual driving energy consumption. MATLAB is used to simulate 20,000 sets of objective factors related to index data and actual driving energy consumption across various models, roads, and environmental conditions, with selected data samples outlined in Table 3.

**Table 3.** Index data of objective energy consumption influencing factors and actual driving energy consumption

| Serial No. | *TF* (L/100 km) | *SL* | *IRI* (mm/m) | *I* | *RS* | *AF* (L/100 km) |
|---|---|---|---|---|---|---|
| 1 | 14.4 | 0.36 | 0.76 | 205 | 1 | 16.1 |
| 2 | 11.8 | 5.15 | 0.39 | 55 | 0.91 | 15.1 |
| 3 | 9.3 | 8.66 | 6.03 | 62 | 0.83 | 10.8 |
| 4 | 7.8 | 8.44 | 4.57 | 503 | 0.84 | 10.5 |
| 5 | 6.8 | 10.55 | 7.55 | 412 | 0.51 | 10.2 |

## 3.2 Determine the Total Effect Value

It is necessary to standardize the index data of 20,000 sets of objective factors using a consistent processing method. Subsequently, the weight value of each objective factor needs to be determined through the combination weighting method. The weight values of each objective factor, as determined by the subjective weight method (AHP), objective weight method (entropy weight method), and the combined subjective and objective weight method based on the least squares method, are presented in Table 4.

**Table 4.** Weight values of objective factors

| | Vehicle performance | Road condition | Traffic conditions | Road meteorological environment |
|---|---|---|---|---|
| Subjective weight method | 0.451 | 0.169 | 0.119 | 0.261 |
| Objective weight method | 0.344 | 0.143 | 0.353 | 0.160 |
| Combined weight method | 0.398 | 0.156 | 0.236 | 0.210 |

In the proposed Eco-Driving evaluation model, the total effect value of objective factors on the vehicle's energy consumption needs to be calculated using Eq. (9) and the combination weighting method. The total effect value ($0 < f < 1$) of the objective factors of 20,000 groups of corresponding vehicles on vehicle energy consumption can be calculated. The distribution histogram illustrating the total effect value is presented in Fig. 6.

The normal distribution pattern is evident in Fig. 6, illustrating the overall trend of the total effect value of the objective factors for the 20,000 sets of corresponding vehicles. The rarity of the effect of objective factors on the maximum and minimum energy consumption of vehicles is indicative of alignment with the real-world driving conditions.

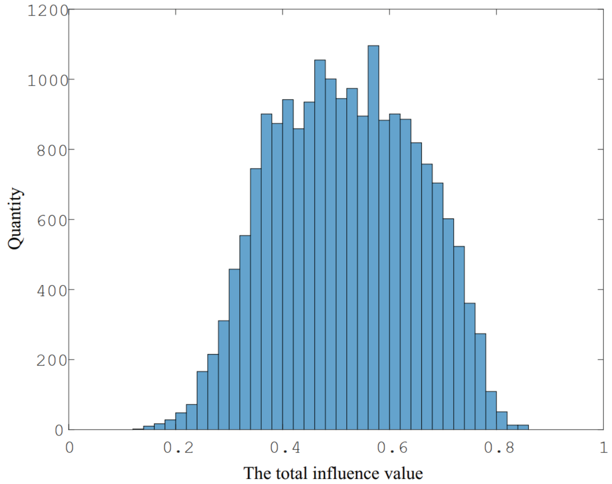


**Fig. 6.** Histogram of total influence value.

# 4. Conclusion

This paper evaluates the cumulative impact of objective factors on vehicle energy consumption. Subsequent cluster analysis of these total influence values facilitates the identification of vehicle clusters sharing similar energy consumption characteristics. Ultimately, this methodology is applied to assess drivers' Eco-Driving performance, paralleling the approach used for vehicle energy analysis.

Eco-Driving evaluation model presented in this paper is versatile, suitable for various vehicles, roads, and environmental conditions. Its simplicity and effective evaluation capabilities are notable advantages. The verification results demonstrate that the evaluation metrics generated by this model accurately reflect the ecological aspects of drivers' conditions. Furthermore, the data derived from this model provides essential support for the future development of Eco-Driving systems, enhancing the analysis of driving behaviors. Additionally, this model contributes to the advancement of gamification-based Eco-Driving systems, offering new avenues for engaging and effective ecological driving strategies.

In this paper, Eco-Driving evaluation model necessitates various types of data, obtainable through onboard terminal equipment and vehicle networking technology. However, this study fails to account for the effect of the air conditioning system and vehicle load while driving. In future studies, it is imperative to gather more efficient data pertaining to objective factors that affect vehicle energy consumption. This will enhance the effectiveness and applicability of the evaluation model.

# Conflict of Interest

The authors declare that they have no competing interests.

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