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Fuel Economy Improvement of Urban Buses with Development of an Eco-Drive Scoring Algorithm Using Machine Learning

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Abstract: Eco-drive is a widely used concept. It can improve fuel economy for different driving behaviors such as vehicle acceleration or accelerator pedal operation, deceleration or coasting while slowing down, and gear shift timing difference. The feasibility of improving the fuel economy of urban buses by applying eco-drive was verified by analyzing data from drivers who achieved high fuel efficiencies in urban buses with a high frequency of acceleration/deceleration and frequent operation. The items that were monitored for eco-drive were: rapid take-off/acceleration/deceleration, accelerator pedal gradient, coasting rate, shift indicator violation, average engine speed, over speed, and gear shifting under low-end engine speed. The monitoring method for each monitored item was set up, and an index was produced using driving data. A fuel economy prediction model was created using machine learning to determine the contribution of each index to the fuel economy. Furthermore, the contribution of each monitoring item was analyzed using the prediction model explainer. Accordingly, points (defined as the eco-drive score) were allocated for each monitoring item. It was verified that this score can represent the eco-drive characteristics based on the relationship between the score and fuel economy. In addition, it resulted in an average annual fuel economy improvement of 12.1%.

Keywords: urban buses; fuel economy; eco-drive system; machine learning

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1. Introduction

Global climate change caused by greenhouse gases has motivated the automobile industry to perform research on CO_2 reduction through improvements in the fuel economy of vehicles. Statistics verify the impact of automobiles on the atmosphere [1–3]. In 2018, road transport accounted for 96.5% of the CO_2 emissions by Korea's transportation sector, which, in turn, accounted for 15.6% of Korea's energy sector [4]. Urban buses are classified as mid-to-heavy duty vehicles. Mid-to-heavy duty vehicles in Korea accounted for 55% of road transport emissions in 2018 [5], whereas the number of registered mid-to-heavy duty vehicles was approximately one-fourth that of passenger vehicles [6]. This illustrates that, as a percentage of the total number of registered vehicles, the CO_2 emissions of mid-to-heavy duty vehicles were relatively higher than those for passenger vehicles. Therefore, a reduction in CO_2 emissions through the improvement of the fuel economy of mid-to-heavy duty vehicles can have a higher impact than a similar reduction for passenger vehicles. This study addresses the concept of eco-drive for improving the fuel economy of urban buses that have a high frequency of acceleration/deceleration and frequent operation. If the fuel economy of approximately 7400 urban buses registered in Seoul (an annual average fuel economy of 2.0 km/m^3) is improved by 10%, economic benefits of approximately KRW 23.8 billion are likely, in addition to improvements in air quality. This assumes an average daily operation of 266 km [7] and the unit CNG (Compressed Natural Gas) price of KRW 730.

This study used machine learning to verify the contribution of items related to fuel economy. Machine learning is used in various research fields such as network security [8], transportation engineering [9], finance and credit rating [10,11], and medical science [12] to establish a relationship between a target value (label) and a wide range of data. In the automobile industry, efforts are being undertaken to use machine learning in areas that incur substantial time and cost. For example, machine learning has been applied to safety and failure detection [13,14], driver classification [15], vibration [16], calibration [17], and system modeling [18], etc. In addition, the need for explainable artificial intelligence has emerged recently, and the predictive model contributions of machine learning features through SHAP (SHapley Additive exPlanations) value [19] are being used [20,21]. In this study, a tool [22] to examine the impact of the tree decision model feature is used.

Eco-drive is a widely used concept that is likely to improve fuel economy through alterations to driving behavior [23] and gear shift strategy [24]. In addition, to promote eco-drive, on-board display methods such as indication through eco-lamps [25] or an indication of the degree of eco-drive by grade for a few items [26–28] may be used. In general, these methods pass on information on eco-driving from a macroscopic perspective. Therefore, in this study, a method for quantitatively determining the driving characteristics that cause inefficient fuel consumption and the potential for improvement was investigated. Furthermore, the effectiveness was verified by the rate of improvement in fuel economy.

2. Relationship between Driving Behavior and Fuel Economy of Urban Buses

In the case of passenger vehicles, the effect of driving habits on fuel economy is widely accepted as the underlying concept of eco-drive. In particular, fuel economy can be improved using eco-drive, e.g., early gear shifting [29,30], inertial energy recovery driving [31], avoiding rapid acceleration of the vehicle [32], and calm driving [33–35]. Through test and driving data analyses of five urban buses, the relationship between these driving behaviors and the fuel economy of urban buses classified as mid-to-heavy duty vehicles was identified. Figure 1a shows that high acceleration reduces fuel economy in urban buses in operation, and Figure 1b shows that rapid deceleration reduces fuel economy. Acceleration is calculated using measured vehicle speed and time. It is evident that as the vehicle speed gradient becomes more intense, the fuel economy decreases.

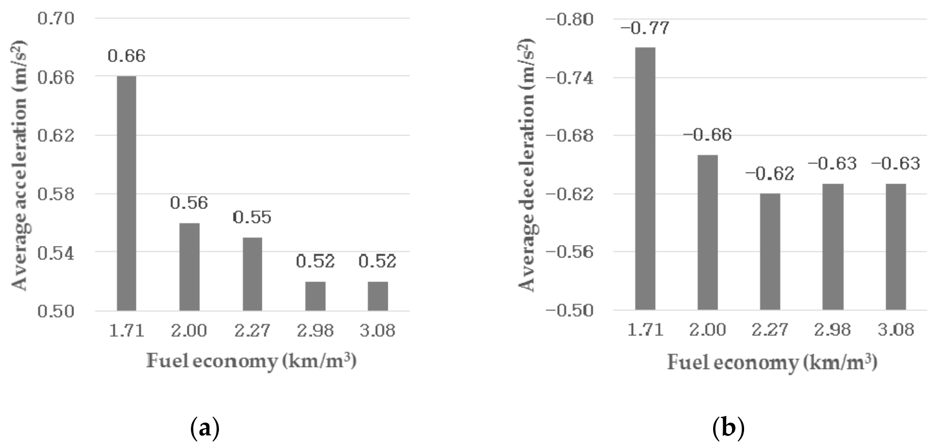


Figure 1. Average vehicle speed gradient: (**a**) average acceleration according to fuel economy; (**b**) average deceleration according to fuel economy.

The recovery rate of inertial energy for eco-drive can be enhanced by increasing the coasting ratio during vehicle stoppage and reducing the energy consumed by the brakes. Through analyzing driving data from two different drivers, it can be shown that a fuel-efficient driver has a higher coasting ratio and gradual speed variation while stopping compared with those of a normal driver. As Figure 2 illustrates, a fuel-efficient driver uses gentle deceleration, including coasting.

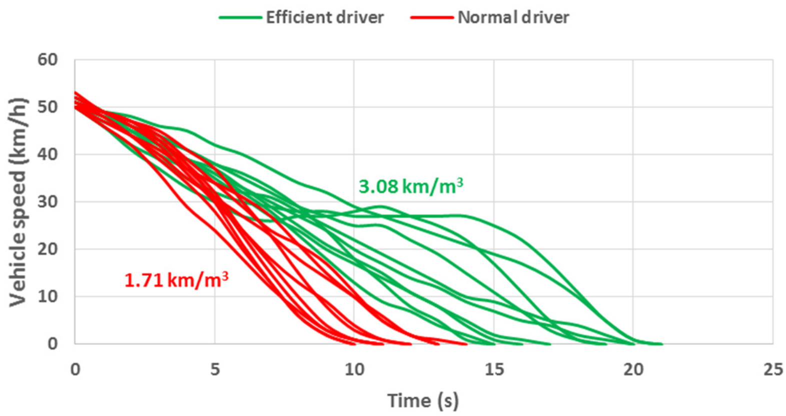


Figure 2. Vehicle speed transition during a stop between an efficient and normal driver at 50 km/h.

Early gear shifting is a technique wherein the shifting of gears for increasing speed while driving is performed earlier. This process induces the engine to enter the low-speed, high-load range by shifting while constant power is generated by the engine. Brake-specific fuel consumption (BSFC, g/kWh) refers to the fuel consumption per unit of engine brake power. BSFC is efficient in the low-speed, high-load range of the engine. Therefore, fuel economy is likely to improve with an early gear shift. As shown in Figure 3, through data analysis of five urban buses, a greater ratio of using the highest gear (5th) and a lower ratio of using low gears increase fuel economy. Therefore, it is necessary to induce fast shifting to the highest gear for better fuel economy.

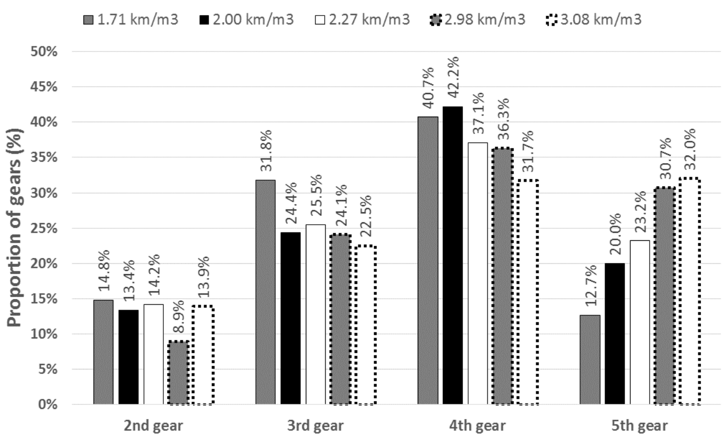


Figure 3. Proportion of gears by fuel economy of buses.

As described above, on-board display devices and ratings for several items are being used for the promotion of eco-drive. However, in this study, the effect on fuel economy improvement was identified through actual vehicle application after segmentation of items for scoring (which can be comprehended intuitively by drivers), setting scoring methods for each item, and allocating points based on machine learning.

3. Index Calculation of Monitoring Items for Eco-Drive Scoring

To promote eco-drive for urban buses, including those discussed in Section 2, rapid take-off/acceleration/deceleration, accelerator pedal gradient, coasting rate, shift indicator violation, average engine speed, over speed, and gear shifting under low-end engine speed were used as monitoring items. An index was calculated for each monitoring item.

Furthermore, a coefficient was multiplied to the index, and an offset was added to it to obtain a score. The total score represents the eco-drive score. The method for calculating each index of the monitoring item was established to score each item using the appropriate coefficient and offset.

3.1. Monitoring Index of Items Related to Speed Variation

An operating characteristic of urban buses is that the number of stop-and-go is significantly higher than that of passenger vehicles owing to bus stops and traffic lights. In addition, rapid acceleration and deceleration occur frequently to ensure arrival within a specified dispatch time or shorten the operation time. In an urban bus having high inertia owing to its relatively high weight and large number of passengers, driving habits that consume a substantial amount of energy while accelerating should be avoided. Therefore, items related to speed variation were divided and monitored as rapid take-off/acceleration/deceleration, accelerator pedal gradient, and coasting rate.

Rapid take-off is a driving habit that adversely affects fuel economy. Therefore, the acceleration at take-off was monitored to improve the fuel economy of the urban bus. Violation monitoring of rapid take-off is performed when certain conditions are satisfied, such as when the accelerator pedal is pressed more than a certain amount during vehicle departure, vehicle speed is below a specific range, and vehicle speed is increasing. A threshold take-off acceleration ($Thd._{launch}$) is set to determine rapid take-off. When the take-off acceleration ($Acc._{launch}$) exceeds the threshold in the monitoring range, the take-off acceleration exceeding rate ($Mark_{launch}$) is calculated and accumulated. The accumulated take-off acceleration exceeding rate is divided by the total number of stops and is used as the rapid take-off index ($Index_{launch}$) (see Equation (1)).

$$\begin{aligned} Mark_{launch} &= \frac{Acc._{launch}}{Thd._{launch}} \\ Index_{launch} &= \frac{\sum Vio._{launch}}{Total\ No.\ of\ stop} \end{aligned} \tag{1}$$

The monitoring of rapid acceleration/deceleration adversely affects fuel economy. Therefore, driving acceleration is monitored by a set standard. The monitoring condition is set above the vehicle speed that can be considered as driving. Furthermore, an acceleration threshold ($Thd._{acc}$) and deceleration threshold ($Thd._{dec}$) are set according to vehicle speed. When the variation in speed ($Acc._{running}$) while driving exceeds the acceleration threshold or deceleration threshold, the acceleration exceeding rate or deceleration exceeding rate, respectively, is calculated (see Equation (2)).

$$\begin{aligned} Mark_{Item} &= \frac{Acc._{running}}{Thd._{Item}} \\ Item\ &: acc,\ dec \end{aligned} \tag{2}$$

The frequent use of the accelerator pedal adversely affects fuel economy owing to the frequent variations in the driving range. The accelerator pedal gradient is monitored every 3 s when the vehicle is being driven without shifting gears. In the monitoring range, the amount of accelerator pedal variation is calculated three times per second. When the accelerator pedal variation amount threshold is exceeded at least once, the highest value from among the three is considered. The exceeding rate of the accelerator pedal variation amount ($Mark_{pedal}$) is set according to the accelerator pedal variation amount. Furthermore, the accelerator pedal variation amount exceeding the rate corresponding to the highest value among the three is calculated.

The coasting rate is monitored to increase the coasting distance ratio during the entire run. The monitoring range is set when the accelerator pedal is not pressed, and the vehicle speed and vehicle speed variation amount for assessing coasting are higher than or equal to their respective thresholds. The coasting distance ($Mark_{coasting}$) in the monitoring range is used to calculate the index.

Among the monitoring items related to speed variation, the index of items, excluding rapid take-off, is calculated by dividing the exceeding rate or distance considered in each case by the total travel distance (see Equation (3)).

$$\begin{gathered} Index_{Item} = \frac{\sum Mark_{Item}}{Total\ distance} \\ Item\ : acc,\ dec,\ pedal,\ coasting \end{gathered} \tag{3}$$

3.2. Monitoring Index of Shift Indicator Operation

For early gear shift, a shift indicator function is installed in the onboard display device of the urban bus. Shift indicator refers to a function that assists in shifting when it is possible to induce driving in the low-speed, high-load range of an engine wherein the engine efficiency is relatively high, and the driving force margin for maintaining driving performance after shifting is secured [36,37]. Figure 4 shows a schematic diagram of the difference in BSFC before and after shifting. For an equal power output, the fuel consumption rate improved after shifting.

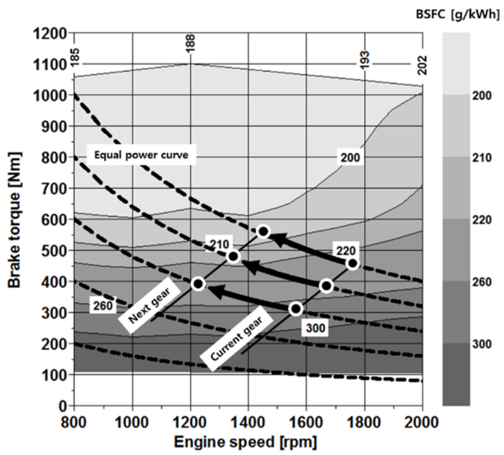


Figure 4. Schematic of brake-specific fuel consumption difference before and after gear shift.

In urban buses, which are mostly manual transmission vehicles, fuel economy can be improved by indicating the appropriate time to shift gears and by using the accelerator pedal position and vehicle acceleration. The engine speed threshold for shifting gears is set up at each gear ratio such that fuel economy is improved and the driving force margin is secured. Shift indicator performance violations are monitored when the current engine speed exceeds the engine speed specified by the shift indicator. When an incline is detected with a high accelerator pedal value and low acceleration, the engine speed threshold is increased to avoid excessive deductions. If the gear is not shifted within 2 s of shift indication, the delay time (seconds) is accumulated and divided by the total driving distance to be used as the shift indicator violation index ($Index_{SI}$).

3.3. Monitoring Index of Other Items

For other eco-drive monitoring items, average engine speed, over speed, and gear shifting under low-end engine speed are used. The average engine speed is monitored to improve fuel economy by limiting operations at high engine speed. The monitoring range for calculating the average engine speed index ($Index_{rpm}$) is the driving condition excluding standstill. However, driving at an engine speed of at least 1000 rpm in the highest gear is excluded from the monitoring range. The sum of engine speeds in the monitoring range is divided by the monitoring time and used as the average engine speed index.

Urban buses travel short distances between stops. Therefore, it is difficult to sustain high speeds while driving. As they have to make frequent stops, it is less necessary to drive above the speed limit of the road. In addition, high-speed driving may increase the risk of accidents, and rapid deceleration when stopping may occur. Therefore, monitoring is performed to limit speeding. The speed limit on the national roads of Korea is generally 80 km/h. The time exceeding 80 km/h is accumulated at every second interval. This is divided by the total travel distance and used as the over speed index ($Index_{vspd}$).

If the gear is shifted at an excessively low engine speed, the vehicle speed is reduced owing to a low driving force margin. A decrease in vehicle speed results in a decrease in engine speed, and driving at an excessively low engine speed may deteriorate vehicle stability. In addition, it is necessary to induce shifting at an appropriate engine speed to prevent damage to the vehicle from shifting gears at a low engine speed to prevent a shift indicator violation. Accordingly, to determine the appropriateness of the engine speed during a shift performed prior to shift indication, if the engine speed is below a threshold, it is monitored after the shift. Monitoring starts if the vehicle is in motion for over 2 s after shifting. The engine speed threshold is set for each gear ratio, and the time (seconds) during which the engine speed is lower than the threshold is accumulated in the monitoring range. The accumulated time is divided by the total travel distance and used as the gear shifting under the low-end engine speed index ($Index_{lowrpm}$).

4. Allocation of Monitoring Item Score Using Machine Learning

4.1. Contribution of Monitoring Item to Fuel Economy through Machine Learning

In this study, a fuel economy prediction model was developed using the machine learning algorithm LightGBM (Guolin Ke, Microsoft Research) to comprehend the fuel economy contribution of the eco-drive monitoring items. LightGBM is a gradient-boosting decision tree framework. It has the advantage of speed improvement through gradient-based one-side sampling (GOSS, which maintains features with large gradients for obtaining prediction information and randomly discards other features) and through exclusive feature bundling (which combines features with high correlation) [38]. In addition, compared with other gradient-boosting techniques of machine learning such as XGBoost (The XGBoost Contributors) and CatBoost (Andrey Gulin, Yandex), LightGBM has high speed without compromising accuracy [39].

A total of 15,000 one-trip driving data of the representative route (Route No. 101) were used. Data preprocessing was performed by removing the outlier for which the magnitude of z-score (which indicates the difference between each data and the average compared with the standard deviation) exceeds three. The preprocessing of the data input to the developed model is a highly important process because it affects the improvement of accuracy. The performance of the model can be improved by input data normalization [40,41], outlier removal [42], and dimension reduction of the feature [43].

LightGBM GOSS-type regression model and five-fold cross-validation were used for modeling. Mean squared error was used as the loss function. The input features of the model are shown in Table 1. The training loss was 0.004.

Table 1. Fuel economy prediction model input features.

Feature	Description	Feature	Description
AccIndex	Rapid take-off index	OverSpeedIndex	Over speed index
Acc2Index	Rapid acceleration Index	SIIndex	Shift indicator violation Index
DecIndex	Rapid deceleration index	ShortAccIndex	Accel. Pedal gradient Index
CoastingIndex	Coasting rate index	PreSIIndex	Shifting under low-end engine speed index
AvgRPMIndex	Avg. engine speed index	-	-

Figure 5 shows an overview of the SHAP value by feature verified by the tree explainer of the model. The distribution of the shift indicator violation index was the widest.

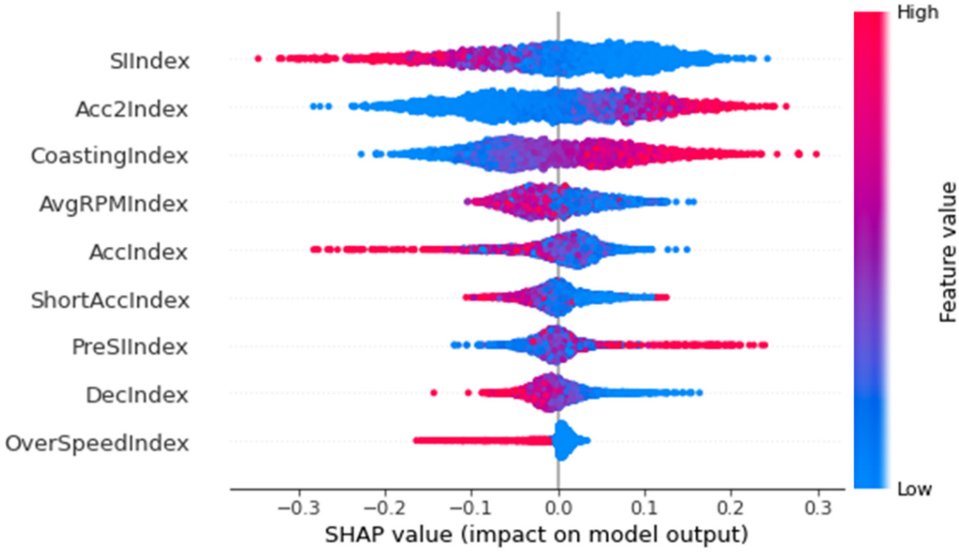


Figure 5. Tree explainer overview of fuel economy prediction model.

The range of the *x*-axis of the overview graph indicates the SHAP value, which shows the contribution of the prediction feature considered interaction between features. The thickness variation shown in the y-direction indicates the distribution, and the contrast variation indicates the amount of feature. Let us consider one of the features, Acc2Index (rapid acceleration index), as an example. Here, the fuel economy improved with a larger data value, and the number of data decreased as the SHAP value shifted away from zero.

4.2. Allocation of Each Monitoring Item Score

The analysis results of the fuel economy prediction model using LightGBM revealed the impact of the monitoring items on fuel economy in the following descending order: shift indicator, rapid acceleration, coasting rate, average engine speed, rapid take-off, accelerator pedal gradient, gear shifting under low-end engine speed, rapid deceleration, and over speed. Using the above results, the score allocation rate was adjusted based on 100 points. The coefficient and offset were set such that the sum of adjusted points according to the index of each item was 100 points. Depending on the circumstances, if a certain item does not have a violation, the coefficient and offset can be set such that starting from zero, points can be deducted. The method of converting the index of each item into a score (the sum of these scores is the eco-drive score) is expressed as Equation (4).

$$\begin{gathered} Score_{Item} = Coefficient_{Item} \times Index_{Item} + Offset_{Item} \\ Eco - drive\ score = \sum Score_{Item} \\ Item\ :\ launce,\ acc,\ dec,\ pedal,\ coasting,\ SI,\ rpm,\ vspd,\ lowrpm \end{gathered} \tag{4}$$

For the eco-drive score set in this study, the indexes of certain items were cumulatively summed (shift indicator violation, rapid take-off/acceleration/deceleration, coasting rate, and average engine speed), and those of others were deducted (accelerator pedal gradient, gear shifting under low-end engine speed, and over speed). Even when the cumulative sum is 100 points, if points are deducted from the deduction items, the eco-drive score would have a lower outcome. Figure 6 shows the point allocation for each item.

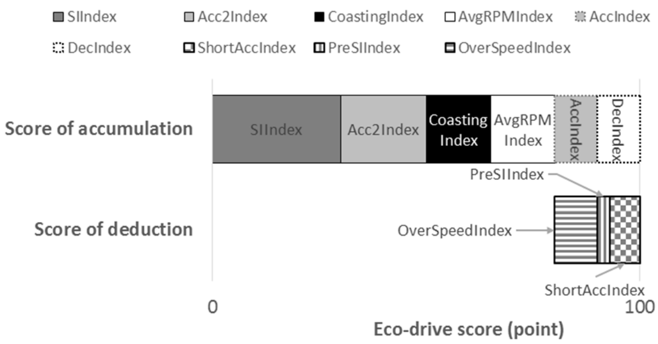


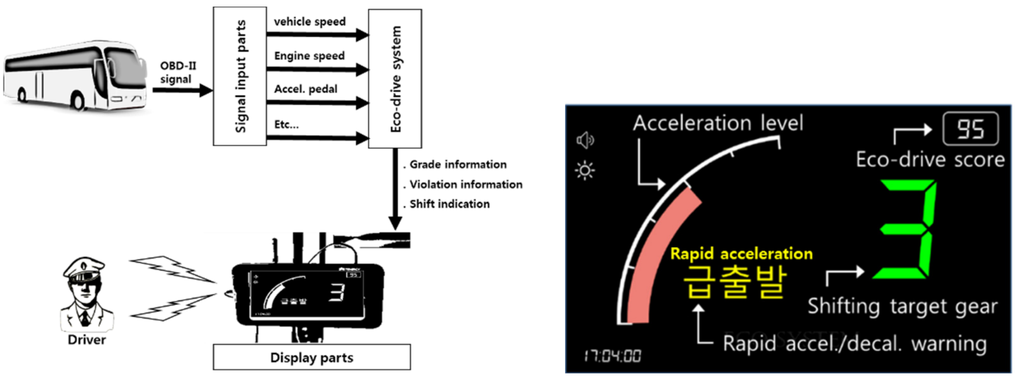
Figure 6. Schematic of eco-drive scoring distribution of each monitoring item.

5. Result

An on-board display device incorporated with an eco-drive score indicator and a shift indicator is defined as the eco-drive system. As shown in Figure 7a,b, devices displaying the shift point/acceleration level/eco-drive score were installed and used on 3864 urban buses on 281 routes in the Urban Buses Fuel Economy Improvement Project hosted by the Seoul Metropolitan Government (see Table 2). These buses operated on assigned routes without shifting. The driver received information about the eco-drive score and shift indicator based on their driving characteristics. Furthermore, the eco-drive score, the index for each monitoring item, and score were saved when driving was completed.

Table 2. Specifications of urban buses.

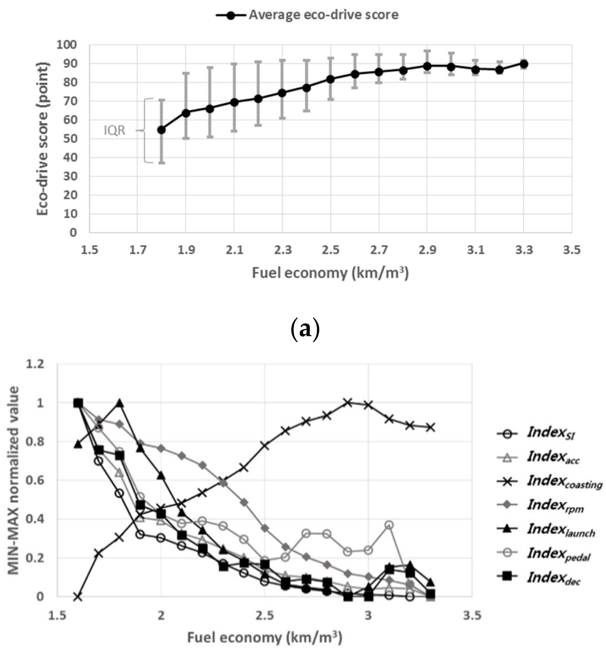
Specifications			
Item		Type 1	Type 2
Engine	Displacement Power Fuel	Inline 6/12,000 cc 290 ps CNG	Inline 6/11,000 cc 290 ps CNG
Vehicle	Transmission Model year Capacity	5-speed manual 2006–2019 25(seat) + 27(stand) + 1(driver)	5-speed manual 2006–2019 26 + 20 + 1



(**a**) (**b**)

Figure 7. Eco-drive system: (**a**) eco-drive system schematic; (**b**) eco-drive system display layout.

A higher eco-drive score was achieved with higher fuel-efficient driving. This implies that the eco-drive score can represent the eco-drive characteristics of urban buses. It is conjectured that the improvement in fuel economy can be maximized through management and enforcement of the eco-drive score. Figure 8a shows the average eco-drive score of 15,000 driving data for 28 buses for each fuel economy value of the representative route, and the IQR represents the 50% range from the median. Figure 8b shows the result of MIN–MAX normalization of the monitoring item index related to the average fuel economy on 15,000 driving data of the representative route. The correlation between each monitoring item and fuel economy can be observed.



(a)

(b)

Figure 8. Tendency of score and indexes: (**a**) average eco-drive score according to fuel economy; (**b**) each monitoring item index normalization value according to fuel economy.

With the display of the eco-drive score, the driver's adaptation period to the eco-drive system shortened, and fuel economy improved. Improvement in fuel economy through the eco-drive score was verified for all seasons. An average annual improvement in fuel economy of 12.1% was achieved. Figure 9 shows the monthly improvement in fuel economy before and after the installation of the eco-drive system during the annual operation on 3864 buses on 281 routes.

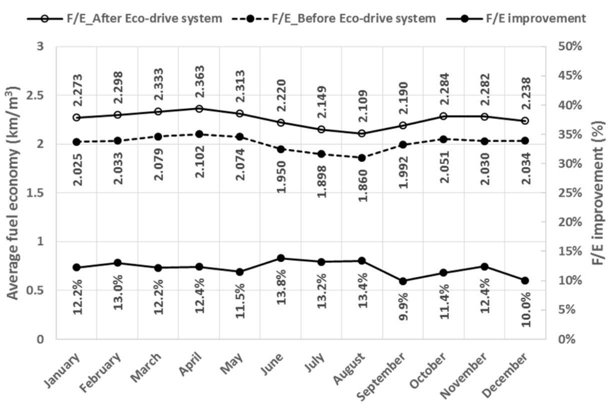


Figure 9. Fuel economy improvement of eco-drive system with eco-drive scoring.

The eco-drive scoring in this study, based on 100 points, has the advantage that the driver can comprehend it intuitively. The rank is subdivided, unlike some that provide grades for only a few items or real-time lighting on an eco-lamp. Hence, it is highly likely that driving habits could undergo transformation because of eco-drive and that the eco-drive score can be managed conveniently. The alteration of driving habits will result in improved fuel economy.

6. Discussion

In this study, the fuel economy of urban busses was improved by applying the eco-drive scoring algorithm. The eco-drive score monitored and scored several driving characteristics related to fuel economy. Monitoring items included vehicle speed gradient, accelerator pedal changes, and gear shift behaviors related to eco-drive. Each monitoring function considered the driving distance in the index calculation. A method that considers the driving distance can represent the violation rate in the total driving range. Through monitoring eco-drive, drivers can avoid aggressive driving and unnecessary braking that negatively impacts fuel economy. Drivers can easily recognize their degree of eco-drive. Previous studies with eco-drive information devices in commercial vehicles have shown an 8.8% fuel economy improvement [27]. In this study, with the application of the eco-drive scoring algorithm, an average annual improvement in fuel economy of 12.1% was achieved in urban buses. These results have shown that fuel economy can be improved by changing driving behaviors without hardware development.

The eco-drive score is displayed based on 100 points, which is the sum of each monitoring item score. In this study, machine learning was used to determine the contribution of input features (monitoring items) in predicting target labels (fuel economy). Each monitoring item score was allocated according to the machine learning contribution result. The score related to shift indicator violations accounted for the highest proportion of the eco-drive score, and scores related to over speed, gear shifting under low-end engine speed, and accelerator pedal gradient were selected as deduction items. The selected deduction items had a low frequency of occurrence. The sum of the scores for each monitoring item was used as the eco-drive score. Through the correlation of the eco-drive score and fuel economy, it has been shown that determining contribution using machine learning is appropriate.

The eco-drive score only considered driving characteristics. However, external factors such as traffic conditions [44,45], traffic light systems [46–48], and the number of passengers can affect driving characteristics and fuel economy. A future study will consider how external factors can be reflected in the eco-drive score.

7. Conclusions

In this study, the eco-drive scoring method was developed to improve fuel economy by promoting eco-drive for urban buses. The improvement in fuel economy (by an average of 12.1% annually) was verified by implementing it on urban buses in Seoul.

Each item for eco-drive monitoring was set such that the score increases when driving behavior shows a tendency to improve fuel economy. Furthermore, the eco-drive score expressed as the sum tends to increase as the fuel economy increases. It can be used to represent the fuel economy of urban bus operations. This scoring process, based on driving behavior characteristics, is likely to promote the application of eco-drive in urban buses, improve fuel economy, and reduce fuel costs.

When it is infeasible to identify a complex relationship with a target value (e.g., comprehending the contribution of each monitoring item of the eco-drive score for allocating points), machine learning can be effectively used to reduce the time and cost incurred.

In this study, the effects of external factors on driving characteristics and fuel economy were not considered in the eco-drive score. In the future, these should be studied in conjunction with the continuous improvement of the eco-drive system.

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Abbreviations

BSFC	Brake specific fuel consumption (g/kWh)
CNG	Compressed natural gas
SHAP	Shapley additive explanations
GOSS	Gradient-based one-side sampling
$Thd._{launch}$	Threshold take-off acceleration (m/s^2)
$Acc._{launch}$	Take-off acceleration (m/s^2)
$Mark_{launch}$	Take-off acceleration exceeding rate
$Index_{launch}$	Rapid take-off index
$Thd._{acc}$	Acceleration threshold (m/s^2)
$Thd._{dec}$	Deceleration threshold (m/s^2)
$Acc._{running}$	Variation in speed (m/s^2)
$Mark_{acc}$	Acceleration exceeding rate
$Mark_{dec}$	Deceleration exceeding rate
$Mark_{pedal}$	Accelerator pedal variation amount exceeding rate
$Mark_{coasting}$	Coasting distance (km)
$Index_{launch}/Score_{launch}$	Rapid take-off index/score
$Index_{acc}/Score_{acc}$	Rapid acceleration index/score
$Index_{dec}/Score_{dec}$	Rapid deceleration index/score
$Index_{pedal}/Score_{pedal}$	Accelerator pedal gradient index/score
$Index_{coasting}/Score_{coasting}$	Coasting rate index/score
$Index_{SI}/Score_{SI}$	Shift indicator violation index/score
$Index_{rpm}/Score_{rpm}$	Average engine speed index/score
$Index_{vspd}/Score_{vspd}$	Over speed index/score
$Index_{lowrpm}/Score_{lowrpm}$	Gear shifting under low-end engine speed index/score
$Coefficient_{Item}$	Coefficient of monitoring item
$Offset_{Item}$	Offset of monitoring item

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