Intelligent Driver System for Improving Fuel Efficiency in Vehicle Fleets

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***Abstract*—A viable solution for increasing fuel efficiency in vehicles is optimizing driver behavior. In our previous work, we proposed a data-driven Intelligent Driver System (IDS), which calculated an optimal driver behavior profile for a fixed route. During operation, the optimal behavior was prompted to the drivers to guide their behavior toward improving fuel efficiency. This system was proposed for fleet vehicles mainly because a small increase in fuel efficiency of fleet vehicles has a significant impact on the economy. The system was tested on a portion of the fleet's route (12km) and achieved 9-20% of fuel saving. One limitation of the IDS was that the prompted behavior profile was the same for all drivers. However, the approach of driving is significantly different from driver to driver. Therefore, it is important to capture those differences in the optimal behavior profile creation and prompting. This paper presents the first steps of a modified IDS that incorporates different approaches of drivers in optimal behavior profile creation. This work has three main components: 1) analyzing the capability of scaling our previously proposed IDS to the complete route of the fleet, 2) assessing the capability of identifying different types of driver behavior from data, and 3) proposing an IDS framework for integrating different driver behavior in optimizing driver behavior. Experimental results showed that the existing IDS was able to achieve 26-37% estimated fuel savings on the complete route. Conclusions of the paper are: 1)the existing IDS scaled to longer routes, and 2) It is possible to identify different driver behavior using data.**

***Index Terms*—Visualization, Fuel Efficiency, Driver Behavior Classification, Eco-driving, Driver feedback**

I. Introduction

Fossil fuel usage has gained increased focus within the past few decades due to limited availability and adverse effects on the environment[1] [2]. It has been identified as one of the primary atmospheric pollutants, which can lead to climate changes [3]. Despite the negative effects, most of the world's energy is provided by fossil fuels. It is the primary energy source which accounts for 80% of the global energy needs [4]. Out of total fossil fuel usage in the US, 71% is used in the transportation section [1]. The demand for fossil fuel shows continuous growth resulting in a continuous increase in its price. Therefore the economic importance of fossil fuel results in an increased focus on fuel efficiency [5].

It has been found that driver behavior has a high influence on fuel efficiency. Therefore, our earlier work proposed an Intelligent Driver System (IDS) and low-cost hardware framework for prompting drivers on a fuel efficient behavior [1]. This worked was focused on a fleet of vehicles because even a small increase in fuel efficiency of fleet vehicles has a significant impact on the economy. The IDS used historical driver behavior data and calculated the optimal (most fuel efficient) driving behavior for a fixed route of 12km. During driving, drivers are encouraged to follow the prompted optimal velocity profile so that driving behavior is controlled to maximize fuel efficiency.

However, it has been found that driver behavior varies between drivers as their driving style is different from one driver to another [6]. Driver style classification is important in wide range of areas including in human-centric vehicle control systems [7], [8], [9], intelligent transportation systems [7], road safety [10] and power management in electric vehicles [11]. The driver style categorization can be done in several ways. In [7], researchers have proposed a mechanism to classify drivers into two categories: aggressive and normal. In [6], researchers have shown that the safe speed (speed preferences) of one driver can be different from the safe speed of another driver. Therefore, they have developed a curve speed model for driver assistance by classifying driver styles into three categories: cautious driving, moderate driving, and aggressive driving.

As discussed above, comfortable driving behavior should be a primary concern when developing an optimal velocity profile, especially in highway route. In such environments, cautious drivers will avoid high speed and hard acceleration while aggressive drivers will prefer higher speeds with large acceleration. Moderate drivers will drive in a steady motion at low accelerations. These three types define the basic expected spectrum of driving behavior in general. Hence, developing a one optimal velocity profile for all the types of drivers might have a negative effect on both fuel efficiency as well as the safety of drivers. Therefore, it is necessary to identify different driver patterns and develop different optimal velocities for different driver categories rather than considering all drivers as similar capabilities.

In this paper, we perform a feasibility study for identifying different driver patterns/clusters with respect to the identified optimal driver behavior. we propose a framework to incorporate driving style clustering, in order to build optimal behavior profiles for different driver clusters. As future work, the proposed driver behavior clustering will be incorporated into the IDS. Further, the proposed system will provide a framework to train drivers gradually, towards the most efficient driver behavior.

This paper has the following contributions:

1) Analyze the scalability of the current IDS by analyzing the fuel efficiency on a longer route.
2) Assessing the capability of identifying different types of driver behavior from data.
3) Propose an IDS framework for incorporating driver behavior clustering which will be implemented in future works.

This paper is organized as follows; Section II discusses the related work. Section III presents the proposed future framework while section IV provides the experimental setup. Section V discusses the results for scalability analysis and the proof of concept. Finally, section VI presents the conclusions and future research directions.

II. Related Work

As discussed in the previous section, increasing fossil fuel efficiency in the transportation sector has become a major research area. In literature, there are three main techniques for improving fuel efficiency in vehicles. They are 1) vehicle technology improvement, 2) traffic infrastructure improvements, and 3) driver behavior changes.

The vehicle technology improvements include improving the physical design of vehicles such as gearbox and engine. It also includes reduction of vehicle weight, improvements of engine efficiency and aerodynamics [12], [1], [13], [14]. However, the main focus of this technique is to reduce CO2 emissions[12], [15].

The traffic infrastructure improvement deal with managing the traffic flow in order to reduce the travel time and vehicle idle time [1]. Therefore, this technique entails followings: 1) construction of roundabouts and traffic lights, 2) imposing speed limits to reduce noise and air pollution, 3) alternate route selection [1], [12].

The third one is driver behavior changes. Despite vehicle manufacturing improvements, fuel efficiency can be significantly reduced if it is badly driven[12]. One viable solution for that is Eco-friendly driving [1]. The idea of this is to change the driver behavior in order to increase fuel efficiency and to reduce the CO2 emission [1] [16],[17]. This technique involves decision making processes under three categories. They are; 1) strategic decisions (vehicle maintenance), 2) tactical decisions (vehicle loading and route selection) and, 3) operational behaviors [18]. Operational behavior is related to less aggressive driving styles, focusing on smooth acceleration and deceleration profile. Less aggressive driving behaviors have a positive effect on fuel efficiency [18], [16], [19]. Eco-friendly driving has reduced fuel consumption by 5-30% [18]. Since driver behavior changes do not require any infrastructure changes, this makes it easy to implements at low cost compared to the other two techniques.

Our previous work proposed an Intelligent Driver System (IDS), which focuses on changing driver behavior to achieve improved fuel economy [20], [1]. This system used historical driver performance data with GPS information in order to build an optimal behavior profile for a fixed route of 12km. A prompting framework of the IDS helps drives to follow the calculated optimal velocity profile. The system was tested on Idaho National Laboratory (INL) bus fleet and was able to increase fuel economy by 9%-20% on a fixed route of 12km. Figure 1 shows the implemented IDS on a real bus. Figure 1 (a) shows prompter of the IDS in an actual bus, whereas Figure 1 (b) shows the GUI of the implemented IDS.

III. Proposed architecture

The architecture of the proposed IDS is presented in **Figure 2**. The fundamental idea behind the proposed architecture was to learn optimal driving behavior using a collection of historical performance data of a set of drivers for a fixed route. Then, different driver styles/clusters will be identified based on the performance of drivers with respect to the optimal behavior profile. Then optimal behavior profiles for different driver clusters will be generated. In future runs, the drivers will be informed the optimal learned behavior based on his/her driver cluster, so that they can adjust their behavior towards the optimal behavior with the goal of increasing the fuel efficiency. The steps of the overall process are presented below.

A. Historical data collection

Sensors of the vehicle are used to extract the information about vehicles' current state. GPS is used to collect the position of the vehicle at a given time. The vehicle information(speed, fuel economy, gear, RPM, instance fuel, cruise speed, etc) and GPS information (latitude, longitude, and elevation) are gathered by the data collector to combine them to provide information about the vehicle at a given instance.

B. Generate the optimal behavior

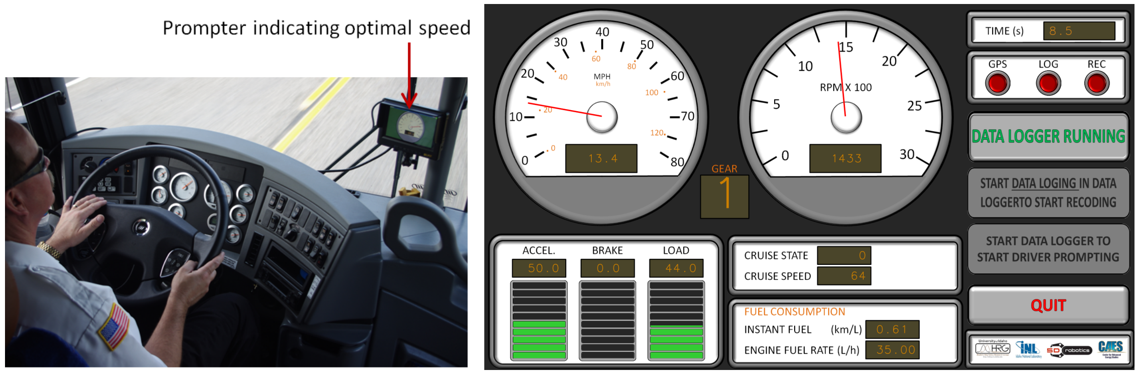
As presented in our previous work [5], the optimal behavior profile is calculated using the data collected in step A.

C. Identify different driver styles/clusters

The driver style clustering can be performed in two different ways,

1) Before calculating optimal behavior from historical data: In this scenario, the driver clustering can be done using driver velocity and driver behavior with respect to road conditions (acceleration, wheel angles, lane departure, etc.) [7].
2) After calculating the optimal behavior profile: In this scenario, it is possible to use drivers velocity profile and behavior wrt road conditions, as well as the deviation between the driver performance profile and calculated optimal behavior profiles.

Different clustering mechanism can be used to identify different types of drivers. The clustering will be performed by using unsupervised machine learning techniques [21]. Simple unsupervised clustering algorithms such as K-Means clustering (K is the number of clusters) [22] [7], Self-Organizing maps [23], and density-based clustering will be used [24] [25]. Further, visual data mining techniques [26] will be used to evaluate the identified driver clusters with the help of human experts.



(a) (b)

Fig. 1. Proposed IDS implemented in INL bus fleet (a) prompter placed in bus cabin (b) GUI of the implemented IDS

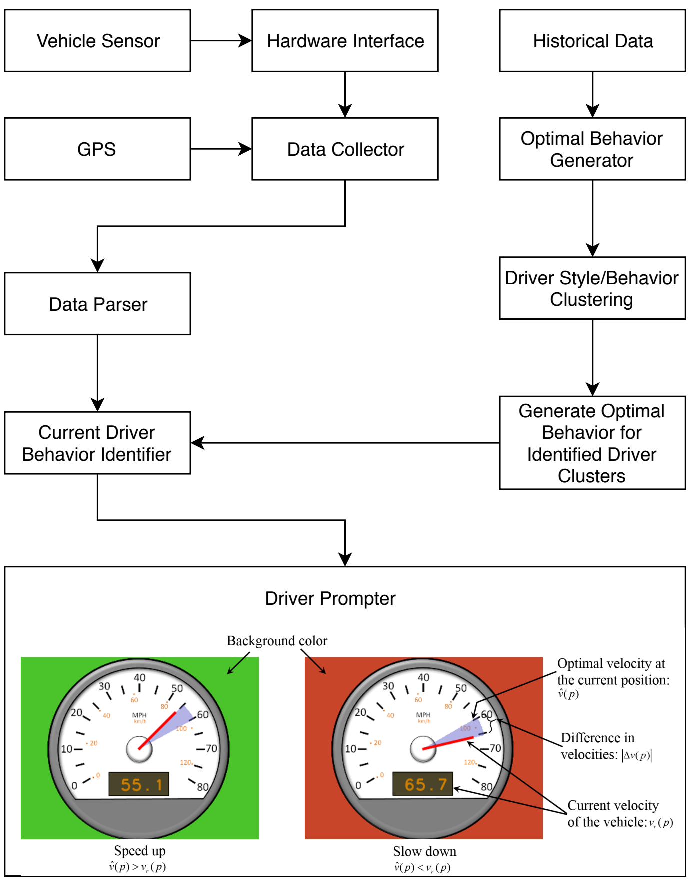


Fig. 2. Proposed Architecture

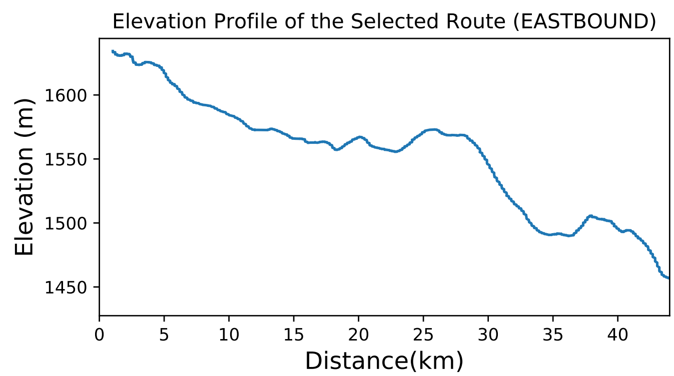


Fig. 3. Elevation Profile

D. Calculate the optimal behavior profiles for identified driver styles

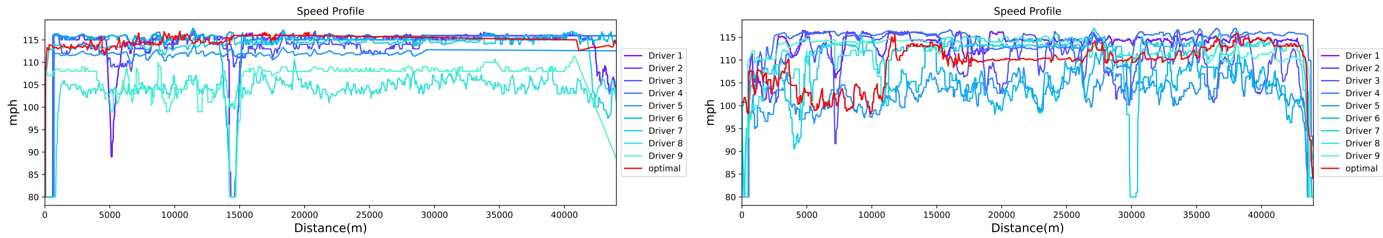
As presented in our previous work [5], optimal driver behavior will be calculated for different driver clusters, which are identified in the previous step.

E. Driver prompting

As presented in our previous work [20], the calculated optimal behavior is presented to the driver through a prompter (See Figure 2, Driver Prompter). The prompter is a small display device which is located on the periphery of the dashboard of the vehicle. Based on the current behavior of the driver/driver style, the optimal behavior profile will be prompted to the driver. The prompter will show drivers' current speed and the speed that they should be driving at. The red line shows the current speed, whereas the blue pie shows the difference between the optimal behavior and the current behavior. So, the driver should accelerate or decelerate in order to reduce the size of the pie as much as possible to maximize fuel efficiency.

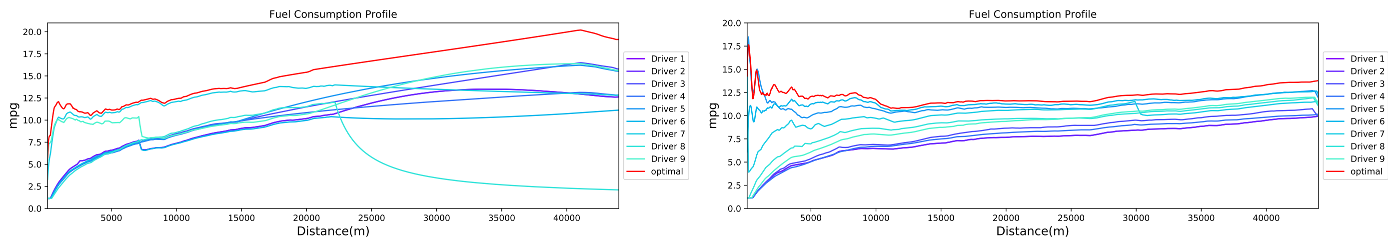
F. Model adaptation

The identified clusters of different drivers and the optimal behavior profiles should be updated over time to maximize fuel efficiency. The fundamental idea here is to train drivers gradually from their comfortable driving style towards a better driving style. Therefore, the divers will be shifted from one cluster to another gradually towards the cluster with most fuel-efficient driver behavior. Further, the historical data set will be updated with time so that newly calculated behaviors will always show better fuel economy than the once calculate before.



(a) (b)

Fig. 4. Speed profiles of different drivers and the calculated optimal velocity (a) Eastbound, (b) Westbound



(a) (b)

Fig. 5. Fuel consumption of different drivers and the calculated optimal fuel consumption profile (a) Eastbound, (b) Westbound

TABLE I
CALCULATED FUEL-SAVING

Direction	Fuel consumption (mpg)				
	Maximum	Minimum	Average	Algorithmic optimal	Fuel-saving %
Westbound	11.1206	9.87534	10.56836	13.3271	26.10
Eastbound	13.8914	9.87534	10.3776	11.6777	37.36

IV. Experimental Setup

This section discusses the experimental setup, data collection process, and details about the collected data.

The architecture proposed in our earlier work was used to collect data for this experiment. The architecture was implemented on a fleet of vehicles of the Idaho National Laboratory (INL) (See Figure 1). The fleet of the vehicle consists of over 90 buses which travel on several routes. For this experiment, the MCI D-series model D4505 buses where selected which run on a fixed route. To check the scalability of the earlier proposed architecture, we selected 44km fixed portion of the US20 West highway in eastern Idaho. This portion was selected due to the following reasons, 1) Consistent traffic, 2) one of the most used routes of the INL bus fleet and 3) Varying elevation profile. The starting point (A) was at lat. 43.3059, long -112.538 and end point (B) was at lat. 43.3089, long -112.216.

Two data sets were collected for the selected portion of fixed route: 1) Eastbound from point A to B, 2) Westbound from point B to A. Eastbound data set consists of a route with a gradually decreasing elevation profile whereas westbound uses the same route in the opposite direction (B to A). Therefore, westbound consists of an elevation profile which increases gradually. Elevation profile of the route from A to B (eastbound direction) is given in **Figure 3**.

For each data set, relevant information such as weather conditions were monitored. For each direction (Eastbound and Westbound), around 16 drivers performance data were recorded. Some of the runs were removed to keep the data sets uniform. The final data sets for Eastbound and Westbound were included of 9 drivers per each.

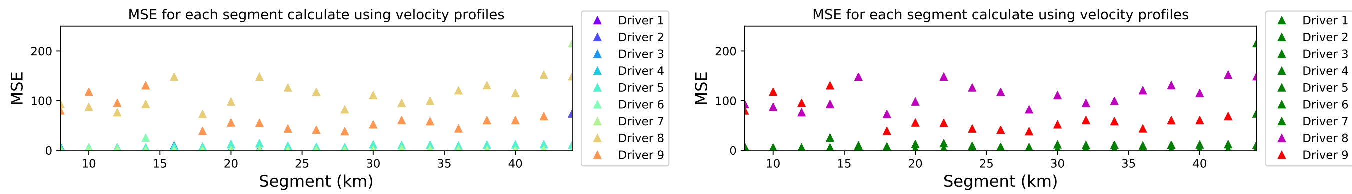
V. Result and Discussion

This section presents the result obtained for this experiment. First, it discusses the scalability of our previously proposed work by calculating the optimal fuel economy on a longer route compared to the 12km route used in previous work. Then, it assesses the capability of identifying different types of driver behavior from data.

A. Scalability of our previously proposed model

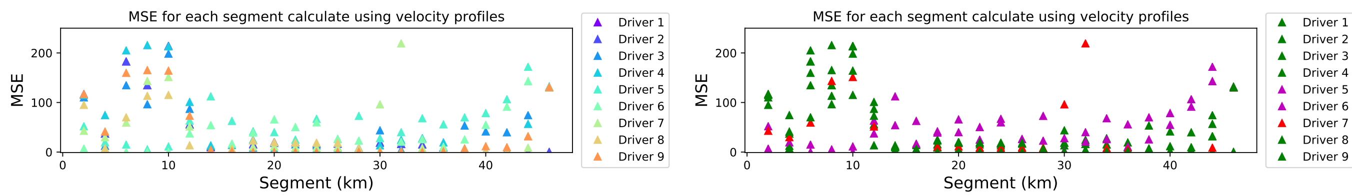
In this experiment, we check the performance of the system on a 44km route.

Figure 4 shows the speed profile-in miles per hour (mph)- for different drivers and the optimal velocity profiles (in red color). For eastbound (Figure 4.a), it can be seen that the calculated optimal profile is very consistent throughout the route. Further, the optimal velocity profile showed a high velocity throughout the route. It might be possible because eastbound has a downhill elevation profile. For westbound (Figure 4.b), the calculated optimal velocity profile exhibits



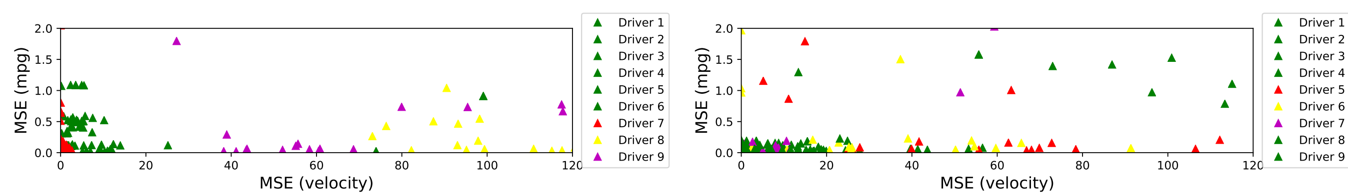
(a) (b)

Fig. 6. Eastbound: MSE of driver velocity vs optimal velocity profile (a) before clustering, (b) after clustering



(a) (b)

Fig. 7. Westbound: MSE of driver velocity vs optimal velocity profile (a) before clustering, (b) after clustering



(a) (b)

Fig. 8. Cluster separation using both the MSE of velocity and MSE of fuel consumption (a) Eastbound, (b) Westbound

large fluctuations. It might be due to the uphill traveling of the fleet in the westbound route.

Figure 5 shows the fuel consumption in miles per gallon (mpg) along the route for each driver (different colors) and the optimal fuel consumption (in red color) which were calculated using IDS. For both eastbound (Figure 5.a) and westbound (Figure 5.b), it can be seen that the calculated optimal fuel consumption profile captures the best behaviors of corresponding historical driver records. Further, it can be noticed that the calculated optimal profile showed a little bit higher fuel economy compared to historical records. It is due to the smoothing function that is used in the IDS [20].

Table I shows the fuel-savings obtained for eastbound and westbound in miles per gallon (mpg). The fuel saving was calculated using the average fuel consumption of all the drivers in a given direction (eastbound or westbound) and algorithmic optimal on that route. For eastbound, the system was able to achieve 37% fuel saving, whereas for westbound, it was 26%. Therefore it can be concluded that the proposed system is scalable to longer routes. In previous work also, it was noticed that eastbound had higher fuel efficiency compared to westbound. This experiment was showed the same pattern. This might be due to the elevation profile difference of the route in opposite directions.

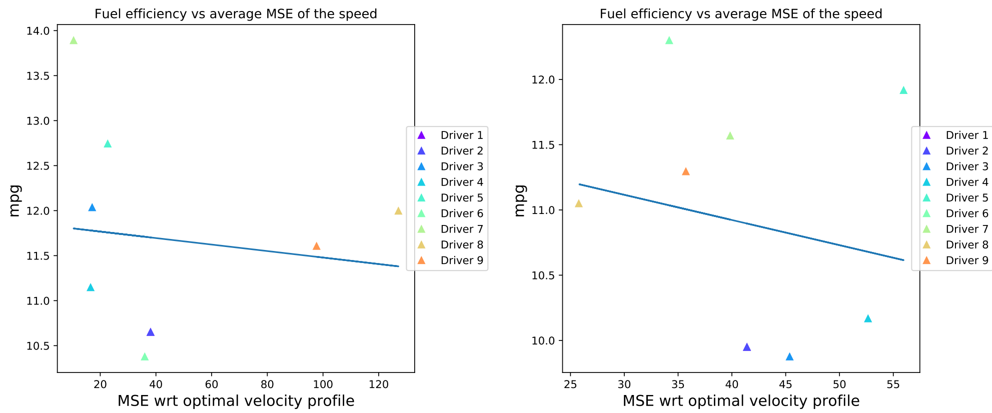
B. Capability of identifying different types of driver behavior

In this paper, we performed a feasibility study to check whether we can visually identify different driver clusters based on the deviation of the driver from the optimal behavior profile. We used data visualization techniques together with unsupervised data clustering methods for evaluating the clusters.

The calculated optimal behavior consisted of two profiles: the optimal velocity profile and the optimal fuel consumption profile. This experiment used these two profiles to calculate the difference of mean square error (MSE) between given driver behavior (velocity and fuel consumption) and the optimal behavior, for each 1km segments along the route. For example, for each 1km segment along the road, the mean velocity for a given driver and the mean velocity of the optimal velocity profile of the corresponding segment was used to calculate the MSE. The MSE is calculated as follows where v is the driver's mean velocity and v' is the mean of optimal velocity for a 1km segment of the road.

$$MSE = \left(v - v^{'}\right)^2 \tag{1}$$

Then MSE values of 1km segments along the road are considered as data records for clustering. Therefore, each driver had set of MSE value for each segment along the fixed route. In the same way, the MSE of fuel consumption



(a) (b)

Fig. 9. Identified trend between the MSE of the velocity of drivers and their corresponding fuel consumption (mpg) (a) Eastbound, (b) Westbound

was calculated for each driver. These MSE value of different drivers were used for driver behavior clustering.

This initial study only investigated the feasibility to use two clustering mechanisms: 1) MSE threshold and, 2) K-Means clusters. In the first method, a machine learning expert can visually analyze the behavior of drivers using the MSE value and define a set of MSE values to cluster drivers. In the second method, the drivers will be clusters based on their relative distance of MSE values.

Figure 6 shows the calculated MSE between the velocity of the drivers and the optimal velocity profile for the eastbound route. Figure 6.a. shows the MSE for each driver, whereas Figure 6.b. shows the cluster assigned to each driver using different colors. Three clusters were identified using k-Mean clustering algorithm. It can be seen that most of the drivers belonged to one cluster (purple). Other two clusters had only one driver record per each. Since MSE values of drivers were highly overlapped, it was not possible to use MSE threshold values to divide the drivers into clusters accurately.

Figure 7 shows the calculated MSE the westbound route. Figure 7.a. shows the MSE for each driver, whereas Figure 7.b. shows the cluster assigned to each driver using different colors. The K-Means clustering was used to assign drivers to different clusters. Even though it assigned the drivers into different clusters, the cluster separation between them was not clearly visible. Further, it was not possible to use MSE threshold values to divide the drivers into accurate clusters. It might be due to the high fluctuations of driver velocity profiles along the westbound route, which resulted in high overlapping of MSE values of the drivers. For both eastbound and westbound, more driver records can result in more precise cluster separations.

Then drivers were clusters using both the MSE of velocity and MSE of fuel consumption. Figure 8 represents the clustering result obtained using the K-means clustering algorithm. Different K values (number of clusters) were tested to obtain proper cluster separations. Figure 8 (a) shows the results obtained for eastbound with k=4. It can be seen that there is a high dense cluster (red and green) near the bottom left corner, which can be identified as one cluster. Figure 8 (b) shows the results obtained for westbound. However, for westbound, it was difficult to identify any cluster separation.

Finally, a degree one polynomial function was used to identify any trend between the MSE of the velocity of drivers and their corresponding fuel consumption. The MSE was calculated for the whole route. Figure 9 shows the result obtained for the identified trend. It can be seen that fuel efficiency decrease when the MSE increases, which was the expected trend, i.e., when MSE increases the fuel efficiency should be decreased. However, more driver records are needed to find a more accurate relationship between them.

VI. Conclusions and Future Work

Driver behavior has a high influence on fuel efficiency. Therefore, our earlier work proposed an Intelligent Driver System (IDS) to calculate fuel-efficient driver behavior (Optimal behavior). The basic idea of the proposed IDS was to change the driver behavior to maximize fuel efficiency. In this work, we investigated the scalability of the IDS on a longer route of 44km. It was found that the IDS is scalable to longer routes. On the selected route, it showed a fuel saving of 26-37%.

Different drivers have different driving styles. Therefore, this work proposed a IDS which calculates different optimal behaviors for different driver clusters rather than calculating one optimal driver behavior for all the drivers. The fundamental idea of the proposed IDS is to change driver behavior gradually by shifting them from one driver cluster to another so that drivers will be shifted towards the most fuel efficient behavior with time. Initial cluster separation of drivers showed that it is feasible to cluster the drivers based on the deviation between drivers behavior and the optimal driver behavior, which was calculated using IDS. Therefore, it implies the necessity to generate several optimal behavior profiles for different driver behavior clusters, rather than calculating one optimal behavior profile for all drivers. However, it was found that more data is needed to identify more accurate clusters.

In future work, the driver behavior clustering will be performed using more driver records. Different clustering mechanism will be implemented, and the proposed IDS will be tested in the INL bus fleet. Further, other factors such as weather conditions and road conditions which influence the fuel economy will be considered.

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