Real-Time Prediction for Future Profile of Car Travel Based on Statistical Data and Greedy Algorithm

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Abstract: Electric Vehicles (EVs) and Plug-in Hybrid Vehicles (PHVs) are expected to be used as power-storage devices in Home Energy Management Systems (HEMSs) due to their high capacity batteries. When planning the charge and discharge of the vehicle’s battery by the HEMS, the expected profile of car’s départures and arrivals for home is required. This paper presents a real-time estimation method for the Profile of Departure and Arrival Times (PDATs) over one day. The PDAT prediction problem is formulated as a maximum-likelihood estimation problem with the probability based on the Statistics of Departure and Arrival Times (SDAT). In the proposed method, the maximum-likelihood estimation problem is decomposed to optimization subproblems, each of which is solved by a greedy algorithm. Due to this decomposition, it is possible to find a plausible solution of the PDAT with a reasonable computational cost. The utility of the proposed method is evaluated by numerical experiments with SDATs derived from the real data of three subjects who use gasoline vehicles.

Key Words: profile of the departure and arrival time, greedy algorithm, maximum-likelihood estimation, energy management system.

1. Introduction

Power storage plays an important role in a Home Energy Management System (HEMS) as part of robust and effective energy management. With the expansion in Electric Vehicles (EVs) and Plug-in Hybrid Vehicles (PHVs) in transportation, it is expected that their high capacity batteries are used for energy storage in the home (e.g. [1]). Charging and discharging between the batteries and home can balance an excess or shortage of energy at home. However, when we use a vehicle’s battery as an HEMS, we must remember that the vehicle is primarily used as a car. The HEMS can manage the battery’s charge and discharge only when the vehicle is connected to the vehicle battery charger. In addition, the HEMS must supply sufficient electricity to the battery by the time the vehicle departs the home. In this situation, the HEMS is required to intelligently plan the timing and battery charge profile taking vehicle use into consideration.

When planning the charge and discharge of the vehicle’s battery, we must first know the car’s future Profile of Departure and Arrival Time (PDAT). In [2], the charge timings are scheduled according to a predetermined PDAT. The PDAT may be available if the user provides departure and arrival times to the HEMS in advance. However, daily car usage frequently changes due to user intent, traffic conditions, and unplanned events. The HEMS must replan charge and discharge every time the PDAT changes. In practice, it is not realistic to assume that a user will always supply the future PDAT to the HEMS. The HEMS must automatically predict the PDAT in real time, on the basis of both the present state of the vehicle, and the statistical data derived from previous use.

Some studies have attempted to estimate a car’s PDAT. Shahidinejad et al. [3] and Ashtari et al. [4] investigated the PDATs of cars used in a city. Their research aimed to investigate the impact on the power grid of charging a massive number of EVs and PHVs simultaneously in a city. Such analysis is important for determining the specification of EVs and PHVs, and to design infrastructure such as charging station deployment across the city [5]. However, these methods cannot predict the profile of an individual car.

Wu et al. [6] and Chen et al. [7] predicted destination travel time on the basis of statistical analysis of historical departure and arrival times, and current traffic conditions. These methods are essential for car navigation systems but do not cover predicting the car’s departure time. Ettema et al. [8],[9] have estimated the PDAT of the car on the basis of a trip and activity utility model. However, their methods do not predict the PDAT in real time, responding to the present patterns of vehicle usage.

In this paper, the authors propose a method to predict the PDAT of individual cars in real time, according to the current state and statistical patterns of car use. The vehicle’s PDAT can be represented as a binary pattern, wherein the car is being used as a car (1) or a storage device (0) in HEMS (Fig. 1). If the authors represent the PDAT over 24 hours as periods of 30 min

Fig. 1 Profile of the Departure and Arrival Time (PDAT) through one day from the present time t.
(48 steps), the number of possible combinations for the binary representation is $2^{48} = 2.8 \times 10^{14}$. In this paper, the problem of predicting the PDAT is formulated as a maximum-likelihood estimation problem, under the condition that both Statistics of the Departure and Arrival Time (SDAT), and the current state of the car are available. To find a feasible solution within a reasonable computational cost, the maximum-likelihood estimation problem is decomposed into optimization subproblems. Then, a greedy algorithm is applied to solve the subproblems in a stepwise manner [10].

The remainder of this paper is organized as follows. Section 2 explains the frequency distribution of car travel as the SDAT of an individual car. The prediction problem is formulated in Sec. 3 and a solution method based on a greedy algorithm is described in Sec. 4. The utility of the proposed method is verified and discussed through some numerical experiments in Sec. 5, and the authors conclude this paper in Sec. 7.

2. Frequency Distribution of Car Usage

The authors denote the car’s state of being available as a battery by an ‘available’ state, and denote a state of being used for transportation by an ‘unavailable’ state. The unavailable state is expressed as a combination of the time at which the car leaves home and the time it returns. Figure 1 shows a sample of the PDAT together with the available and unavailable states. The $i$-th departure time from the present time is represented as $s_i$, and its arrival time is $e_i$. Note that only hatched components can take non-zero values in Fig. 1. Here, one day is divided into $T$ steps.

The SDAT is described by a frequency distribution table such as Table 1. This table is derived from the car’s daily PDAT, wherein the column represents the car’s departure time and the row represents the arrival time. Here, the authors use 6:00 a.m. as the SDAT start time. We exclude data where the time before returning exceeds $T$. Thus, the number of rows goes from 1 to $2T - 1$.

The PDAT is predicted by the frequency distribution table transformed from the SDAT on the basis of the current time. An element of the SDAT at $e$-th row and $s$-th column is represented as $M(e, s)$, and a periodic matrix $A \in \mathbb{Z}^{\infty \times \infty}$ which has a representation is $2^{48}$ with the periodic matrix $A$ as follows:

$$A(e + aT, s + aT) = \begin{cases} M(e, s) & \text{if } 1 \leq e \leq 2T - 1, 1 \leq s \leq T, \\ 0 & \text{otherwise.} \end{cases}$$

Then, the authors calculate frequency distribution matrices with the periodic matrix $A$ to predict the PDAT for each time $t$. A frequency distribution matrix $A'$ is generated with the periodic matrix $A$ as follows:

$$A'(e, s) = A(e + t - 1, s + t - 1),$$

$$\text{if } 1 \leq e \leq 2T - 1, 1 \leq s \leq T.$$  (2)

Equation (2) demonstrates that the matrix $A'$ is extracted for the time period $(2T - 1) \times T$ from the periodic matrix $A$ at time $t$. In other words, the matrix $A'$ is generated with the frequency distribution table for the current time as the reference point considering the time periodicity.

3. Formulation of the PDAT Prediction Problem

3.1 Definition of Variables

Variables for the prediction problem are defined as follows:

$i$: identification labels for car travels, $i \in \{1, \ldots, k\}$, $k$: an upper bound of car travels for a day, $T$: the number of one day steps, $t$: the current time index, $t \in \mathbb{Z}$, $A$: the periodic matrix generated by Equation (1) with the SDAT, $A \in \mathbb{Z}^{\infty \times \infty}$, $A'$: frequency distribution matrices on the basis of $t$, $A' \in \mathbb{Z}^{(2T-1) \times T}$, $t'$: the departure time of the last car travel, $t' \in \mathbb{Z}$, $S'_{ik}$: random variables for the $i$-th departure time at $t'$, its realized value is $s_i \in \{-T, \ldots, T\}$, $E'_{ik}$: random variables for the $i$-th arrival time at $t'$, its realized value is $e_i \in \{1, \ldots, 2T - 1\}$, $a'_{ij}$: an element at $e$-th row and $s$-th column of $A'$, $\gamma'$: the car state for the travel at the current time $t$, $0(1)$ means a car is the available (unavailable) state, $\gamma' \in \{0, 1\}$.

3.2 Prediction Problem Based on Optimization

The authors formulate the prediction problem of the car’s $k$ travel times as a simultaneous optimization problem as follows. A simultaneous optimization for PDAT

**Given**: $A'$, $t'$, $\gamma'$, $k$

**find**: $(s_1, e_1), \ldots, (s_k, e_k)$

**which maximize**:

$$J = P(S'_{1t'}, E'_{1t'}) = (s_1, e_1), \ldots, (S'_{kt'}, E'_{kt'}) = (s_k, e_k) | A'),$$  (3)

**subject to**:

$$\forall i \in \{1, \ldots, k\} \forall j \in \{1, \ldots, k\} \setminus \{i\} \{ [s_i, e_i] \cap [s_j, e_j] = \phi \},$$  (4)

$$\exists i \in \{1, \ldots, k\} \ (s_i = t' - t) \text{ if } \gamma' = 1.$$  (5)

In Equation (3), $P(y|x)$ is a conditional probability that event [2] The matrices $A'$ are not the periodic matrices.

The matrices $A'$ are not the periodic matrices.
y will occur if event x is realized. Equation (3) shows the occurrence probability for the PDAT, and Equations (4) and (5) are constraints related to the time scheduling. Equation (4) is to prevent several car travels occurring at the same time. When the car is absent from home at time t (γ′ = 1), the first departure time is set to t′ − t by condition (5).

### 3.3 Flowchart for Real Time Maximum Likelihood Estimation

The optimization problem must be solved in real time. The prediction process is shown as a flowchart in Fig. 2. The flowchart illustrates the procedure for real time maximum likelihood estimation. At the beginning of the calculation in our algorithm, time t is initialized to the current time.

First, in each time t, the car’s current state is observed (home/absent), and the car’s state γ is updated. If the car is absent (γ′ = 1), the last departure time t′ is also updated. Second, the frequency distribution matrix A′ is calculated. Finally, the authors solve the optimization problems described in Equation (3). Using the results, we can predict the PDAT.

### 4. Proposed Method Based on a Greedy Algorithm

The computational complexity of this optimization problem depends on the search space of the probability in Equation (3). Unfortunately, this problem has a high computational complexity because it is a combinatorial optimization problem concerned with the car travel times k. The search space has the exponential order O(T^2k) (the number of steps of one day T is 48). This problem is very large to solve by calculation. Computational complexity is a major concern.

Therefore, the authors propose a search algorithm to obtain semi-optimal solutions to the combinatorial optimization problem by solving subproblems separated from the original by a greedy algorithm. We can find a solution by merging sub-solutions that have the maximum profit for each subproblem. With our proposed method, the computational cost decreases by linear order O(T) in time complexity because the search space is divided by the greedy algorithm.

For the formulation of the subproblems, the evaluation function (3) is expanded as follows:

\[
P(S_i^1, E_i^1) = (s_i, e_i), \ldots, (S_i^{l_i}, E_i^{l_i}) = (s_i, e_i)|A'] = P(S_i^{l_i}, E_i^{l_i}) = (s_i, e_i)|A'] \\
\times P(S_i^{l_i}, E_i^{l_i}) = (s_i, e_i)|A'] \times \ldots \\
\times P(S_i^1, E_i^1) = (s_i, e_i)|S_i^1, E_i^1), \ldots, (S_i^{l_i}, E_i^{l_i}), A' = J_1 \times \cdots \times J_k. \tag{6}
\]

For \( i = 1, \ldots, k \), the evaluation functions \( J_i \) of the subproblems is represented as follows:

\[
J_i = P(S_i^j, E_i^j) = (s_i, e_i) \cdot (S_i^{j+1}, E_i^{j+1}), A'), \tag{7}
\]

where \( J_i \) is the occurrence probability of car travel \( i \) under the condition that the other car travel labeled 1, 2, \ldots, \( i - 1 \) occur. Then, the \( i \)-th car travel is selected by maximizing \( J_i \) without overlapping other periods at the constraint (4).

Given car’s state, subproblems must be divided into the two cases: \( \gamma' = 1 \) and \( \gamma' = 0 \). This reason is why \( s_i \) depends on \( \gamma' \) by constraint (5). When the car is absent (\( \gamma' = 1 \)), only the arrival time for the last travel is predicted by the subproblem.

When the car is at home (\( \gamma' = 0 \)), a pair of departure and arrival times are predicted. Then, we formulate these subproblems as follows.

**B-1. sub-optimization problem (\( \gamma' = 0 \))**

\[
\text{Given} : A'_{ij}, (s_j, e_j)_{j=1, \ldots, l} \\
\text{find} : (s_i, e_i),
\]

which maximize : 

\[
J_i = P(S_i^j, E_i^j) = (s_i, e_i) | (S_i^{j+1}, E_i^{j+1}), A'), \tag{8}
\]

subject to:

\[
\forall j \in \{1, 2, \ldots, i-1\} \{ (s_i, e_i) \cap (s_j, e_j) = \phi \}. \tag{9}
\]

In this problem, the departure and arrival times are found using the condition (9), which prevents travels from overlapping. In the case of \( \gamma' = 1 \), only the arrival time is found in the subproblem when the last departure time is \( t' \). Hence, given the frequency distribution matrix A′ at the time \( t' \), we formulate the subproblem as follows.

**B-2. sub-optimization problem (\( \gamma' = 1 \))**

\[
\text{Given} : t', A', e_1, \tag{10}
\]

which maximize : 

\[
J_1 = P(E_i^l = e_i | S_i^1 = s_i, A') \tag{11}
\]

In this problem, the arrival time \( e_i \) is found on the basis of the last departure time \( t' \) from Equation (11). Because subproblem B-2 determines the arrival time when the departure time is given, the departure and the arrival time of car travels from \( i = 2 \) to \( k \) are determined by the subproblem B-1.

Figure 3 is the greedy algorithm flowchart that illustrates the prediction process of car travels up to k times at time t. Initially, the value of \( \gamma' \) is checked and set to either zero or one to select the relevant subproblem. If \( \gamma' = 0 \), the subproblem B-1 is selected and the car travel (\( s_i, e_i \)) is decided from \( i = 1 \) until the completion condition is satisfied. In the completion check, the prediction procedure is abandoned when \( i > k \) or the occurrence probability \( J_i \) is less than threshold value \( P_{\text{min}} \). In contrast, if \( \gamma' = 1 \), the arrival time \( e_i \) is selected in the subproblem B-2 on the basis of last departure time \( t' \), and the subproblem B-1 is solved for each \( i \) from \( i = 2 \). Finally, the predicted PDAT com-
posed of several car travels can be obtained from our proposed algorithm.

The occurrence probabilities for car travel are calculated with the frequency distribution matrices \( A_t \). At the first iteration in Fig. 3, the evaluation function (8) in the subproblem B-1 is calculated as follows:

\[
J_1 = P(S_t^1, E_t^1) = \sum_{e} \sum_{s} a_{te}^1, s_1.
\] (12)

In the subproblem B-2, given departure time \( t' \), the evaluation function (10) is calculated as follows:

\[
J_1 = P(E_t^1 = e_1 | S_t^1 = s_1, A_t) = \sum_{e} a_{te}^1, e_1, s_1.
\] (13)

From the second iteration \( (i = 2, 3, \ldots, k) \) in Fig. 3, the car travel is predicted by subproblem B-1. Then, the predicted car travels \( (s_j, e_j) \) \((j \leq i - 1)\) are already obtained, and subproblem B-1 is constrained by Equation (9). To express constraint (9), the frequency distribution matrix \( A_t^i \) is defined as follows:

\[
a_{te}^i = \begin{cases} 0, & \text{if } (s, e) \in \{(\hat{s}, \hat{e}) | j < i, (\hat{s} \leq e_j) \wedge (\hat{e} \geq e_j)\}, \\ a_{te}, & \text{otherwise}, \end{cases}
\] (14)

\[
a_{te} = \begin{cases} 0, & \text{if } (s, e) \in \{(\hat{s}, \hat{e}) | j < i, (\hat{s} \leq e_j) \wedge (\hat{e} \geq e_j)\}, \\ a_{te}, & \text{otherwise}, \end{cases}
\] (15)

where Equation (14) is essential to avoid multiple simultaneous car travels. Consequently, the occurrence probability (8) of \( i \)-th car travel in the sub-optimization problem B-1 is calculated as follows:

\[
J_i = \frac{\sum_{e} \sum_{s} a_{te}^i, s_1}{\sum_{e} \sum_{s} a_{te}^i, s_1}.
\] (16)

Figure 4 shows how the search range is reduced by the frequency distribution matrices \( A_t^i \). By this reduction, it is expected that the computational complexity of the PDAT prediction is decreased.

5. Computational Experiments

5.1 Settings

The authors collected PDATs for approximately 380 days from three gasoline cars owned by three different families. Subject A is a woman who mainly uses a car to commute to her workplace. Subject B is a young couple who mainly use a car for shopping and taking a child to and from kindergarten. Subject C is a middle-aged woman who mainly uses a car for shopping.

To collect PDAT data, the authors used GPS loggers that can record time and location data while the engine is running. On the basis of the obtained data, we extracted the time pairs at which each subject departs and arrives back at his/her home.

Car travel frequency distributions for the subjects are depicted in Figs. 5, 6, and 7, respectively. In addition, details of the data used to make the frequency distributions is shown in Table 2. This includes the number of sample days, total frequency, and average travel time. These distributions are made from data covering approximately 350 days. The remaining 30 days data used for verification. The authors conducted the pre-
Table 2  Travel times for measurement days.

<table>
<thead>
<tr>
<th>Subject</th>
<th># of sample days</th>
<th>total frequency</th>
<th>Average travel time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>355</td>
<td>414</td>
<td>8.53</td>
</tr>
<tr>
<td>Subject B</td>
<td>349</td>
<td>174</td>
<td>12.07</td>
</tr>
<tr>
<td>Subject C</td>
<td>355</td>
<td>173</td>
<td>7.09</td>
</tr>
</tbody>
</table>

The predicted PDATs and verification data for subject A from \( t = 1 \) to 13 in a day are depicted in Fig. 8. Figure 9 is the predicted PDATs from \( t = 14 \) to 26 of subject B. The horizontal axis shows time. The dashed line is the predicted PDAT and the solid line is the verification data.

In Fig. 8, the predicted result for subject A matches the verification data well. In contrast, the errors between the prediction and verification PDATs in Fig. 9 is large. This is because subject A uses the car in a relatively the regular manner, whereas subject B does not. Figure 9, we can see the adjustment of the predicted profiles between \( t = 16 \) and 17, \( t = 21 \) and 22, respectively. These are caused by the contradiction between the predicted and the observed present car states \( \gamma_t \). The adjustments are successfully executed in the procedure of subproblem B-2.

To analyze the statistical performance in predicting PDATs, the authors define the agreement rate at \( t \) as follows:

\[
\sigma(t) = \frac{\sum_{m=1}^{T} \left( \delta_{00}(\gamma(m|t), \hat{\gamma}(m)) + \delta_{11}(\gamma(m|t), \hat{\gamma}(m)) \right)}{\eta(t) + \epsilon(t)},
\]

(17)

where

\[
\eta(t) = \sum_{m=1}^{T} \left[ \delta_{00}(\gamma(m|t), \hat{\gamma}(m)) + \delta_{10}(\gamma(m|t), \hat{\gamma}(m)) \right],
\]

(18)

\[
\epsilon(t) = \sum_{m=1}^{T} \left[ \delta_{01}(\gamma(m|t), \hat{\gamma}(m)) + \delta_{11}(\gamma(m|t), \hat{\gamma}(m)) \right].
\]

(19)

\( \gamma(m|t) \in \{0, 1\} \) is the car’s state at time \( m \) predicted at time \( t \), \( \hat{\gamma}(m) \) the real car state at time \( m \), and \( \delta_{ij}(x, y) \) is equivalent to Kronecker delta which is defined as follows:

\[
\delta_{ij}(x, y) = \begin{cases} 
1 & \text{if } i = x \text{ and } j = y, \\
0 & \text{otherwise}. 
\end{cases}
\]

(20)

Next, the authors introduce the true positive and negative rates. The true positive rate is defined as follows:

\[
r_p(t) = \frac{1}{\epsilon(t)} \sum_{m=1}^{T} \delta_{11}(\gamma(m|t), \hat{\gamma}(m)).
\]

(21)

The true positive rate is the proportion of correctly predicted periods of actual traveled states (\( \hat{\gamma}(m) = 1 \)). In contrast, the following true negative rate is the proportion of correctly predicted periods of actual staying at home states (\( \hat{\gamma}(m) = 0 \)).

\[
r_n(t) = \frac{1}{\eta(t)} \sum_{m=1}^{T} \delta_{00}(\gamma(m|t), \hat{\gamma}(m)).
\]

(22)
Fig. 9 Prediction of car travel for subject B from $t = 14$ to 26.

Table 3 Average and variance values of agreement rate, true positive rate, and true negative rate for one month.

<table>
<thead>
<tr>
<th></th>
<th>Subject A</th>
<th>Subject B</th>
<th>Subject C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agreement</td>
<td>0.834</td>
<td>0.712</td>
<td>0.755</td>
</tr>
<tr>
<td>True positive</td>
<td>0.835</td>
<td>0.704</td>
<td>0.505</td>
</tr>
<tr>
<td>True negative</td>
<td>0.828</td>
<td>0.739</td>
<td>0.787</td>
</tr>
</tbody>
</table>

We calculated the average and variance values of $\sigma(t)$, $r_{tp}(t)$, and $r_{tn}(t)$ using the 30-days verification data. The results are shown in Table 3. Subject A showed the highest average value and the lowest variance value in each rate. The temporal values of the agreement rate and the true positive rate are shown in Figs. 10 and 11 respectively. The true positive rate could not be calculated in the shaded periods because $e(t)$ becomes zero when car travel was not observed during 24 hours (in $T$).

As for the prediction procedure computational time, shown in Fig. 3, the proposed method took approximately 0.1 sec from start to finish. This calculation time is sufficient to predict the PDAT in real time, every 30 min. In contrast, when we solved the simultaneous optimization for the PDAT in straightforward manner, it took 22 hours.

6. Discussion

For the Home Energy Management System (HEMS), which utilizes the car’s battery as home power storage (as described in Sec. 1), the true positive rate is considered the most significant measure to in order to evaluate the predicted results. When the true positive rate is low, the HEMS is likely to plan to charge and discharge the car’s battery when the car is absent. Such plans may mean operating of HEMS is infeasible. In other words, the HEMS cannot charge and discharge the battery within the required constraints; for example, the charge ratio limitation and the minimum amount of electricity stored in the battery. In contrast, the low true negative rate does not
make operating HEMS into infeasible. It only reduces usage ratio of the car’s battery in HEMS. From this viewpoint, the predicted result of subject A has the highest performance, as shown in Table 3.

The reason for the high performance of subject A is that she uses the car in the most regular manner of all subjects. This regularity is shown in her SDAT Fig. 5. If statistical regularity is difficult to determine in the SDAT, the prediction cannot perform well. How then should we deal with variation in car travel? One solution is to switch to multiple frequency distributions depending on features affecting the user’s car travel behavior. For example, the significant difference between the PDATs of weekdays and holidays is reported in [3]. The effect of the difference can be observed in Figs. 10 (a) and 11 (a). The agreement and true positive rates in holidays are lower than ones for weekdays. Implementing multiple frequency distributions to the proposed prediction framework will be studied as future work.

We employed a frequency distribution as the SDAT whose instances are departure and arrival time pairs. This is because the number of instances to be considered is only \( T^2 \). If we used a frequency distribution with instances as the PDATs, we would have frequency distribution for \( 2^T \) instances. However, because people only travel by car several times a day, (except using the car for work), it takes long time to obtain a frequency distribution with sufficient precision. How much precision is required of the frequency distribution to achieve good prediction performance? Figure 12 shows the prediction result for subject A when the number of learning data for the frequency distribution is changed. The rates do not change much as the number of learning data. In the proposed method, the greedy algorithm selects the maximum points as the most plausible pairs of departure and arrival times. Therefore, as the maximum points are unchanged, the prediction results do not change even if the number of learning data is low. Of course, this characteristic depends on the SDAT which represents trends in car travel. In the case of subject A, the characteristics were achieved since she used the car in a regular manner. In contrast, we can get the result that subject C does not have the characteristics from Fig. 13 due to irregular manner of her car travel.

7. Conclusion

This paper presented a method for estimating the Profile of Departure and Arrival Times (PDATs) for a car over one day. It was based on the Statistics of Departure and Arrival Time (SDAT) and a greedy algorithm. The experimental results showed a plausible solution could be found within a reasonable computational time. However, the proposed prediction method is not evaluated in the HEMS, which will be the subject of future work.

This estimation problem is formulated on the basis of a limited observation of the car’s travel state at the current time. This is the necessary minimum as the observation is required to collect SDAT. Accordingly, using other information such as driver schedule and traffic flow, may improve estimation performance.

Prediction result performance depends on the distribution profile of the SDAT. If the SDAT has statistical regularity, the prediction produces good results, because this method predicts a PDAT based on collected data. In the opposite case, PDAT's
are not predicted with accuracy. One solution strategy for this issue is to divide the SDAT into working day and holiday categories. This division should be determined carefully by considering the driver’s lifestyle, and will comprise future research for our team.

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