

A probabilistic range estimation method for electric vehicle with dynamic traffic information

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Summary

The accessible range for the Electric Vehicle (EV) is related to travelling energy consumption along the trip, which is directly influenced by the changing traffic environment. A proper remaining range estimation method should reflect the changing feature of traffic system. In this paper, a probabilistic range estimation method is proposed based on the time-dependent stochastic traffic model, and stochastic simulation-based Genetic Algorithm is applied to evaluate the driving energy consumption, and therefore, EV accessible range can be estimated by the stochastic programming analysis model. Simulation comparison with two other range estimation methods proves that the proposed method receives an estimation result with higher accuracy and low variation in most simulation scenarios, which indicates the advantage of the proposed method.

Keywords: BEV(battery electric vehicle), energy consumption, range, state of charge, simulation

1. Introduction

In recent years, electric vehicles (EVs) are becoming an effective solution to mitigate the global warming and the exhaustion of fossil fuels. Unfortunately, being afraid of running out of energy while the EV is far from any charging station, the so-called ‘range anxiety’, is the major concern among EV drivers [1, 2]. In order to alleviate anxiety caused by the limited range of EVs, an accurate remaining mileage estimation is essential because a valid assessment result would encourage the driver to plan their trip and enhance consumer confidence in EVs.

In general, there are two methods to estimate the remaining range for EVs. The first way is based on the travelling energy consumption history. The basic idea is to find the relationship between past travelling distance and past energy consumption. Ceraolo, M. acquired the battery remaining energy based on average battery voltage and current battery charge, and then calculated the ratios between the distance and energy consumption which is used to estimate the remaining accessible distance[3, 4]. Shuai, Z. calculated the result of current vehicle velocity divided by the motor power and then use this value multiplied by current remain battery energy to evaluate the remaining mileage[5]. The relationship between state of charge(SOC) and distance were established by Kayano, M. and Cho, I. to obtain the residual range for EV[6, 7, 8].

Besides the method based on the distance-energy or distance-SOC ratio, the other way considers the future energy consumption along the route. Zhang, Y proposed the EV energy consumption algorithms consisting of propulsion energy consumption and electric device energy consumption, and then take the current traffic information as input to predict the energy consumption[9]. Typical urban driving cycle ECE+EUDC was

utilized to match the coefficient between the velocity and energy consumption, and then the energy consumption was predicted according to the departure time and current road traffic[10].

These two methods treated the future traffic environment to be similar to the previous or current traffic environment. However, these studies did not consider the stochastic changing feature of the traffic environment, which is inconsistent with the real traffic. Therefore, a reasonable method is ought to consider the changing and random properties of the traffic system to guarantee a more credible range prediction result.

The main contribution of this paper is to propose a framework to integrate the changing feature of traffic information into the range estimation problem. The stochastic simulation-based genetic algorithm (GA) is applied to evaluate the energy consumption. The stochastic changing traffic lead the range estimation result to be a probabilistic status rather than a definite status. Therefore, the reachable area are obtained based on the stochastic programming evaluation standard.

In this paper, Section 2 presents the overall algorithm structure, and Section 3 describes the traffic model. In Section 4 and Section 5, detailed range estimation procedure are explained. In Section 6 and 7, a simulation model is established to evaluate the quality of the proposed method. Finally, some conclusions are drawn in Section 8.

2. System Architecture

Nowadays, along with the rapid development of Intelligent Transportation System (ITS), traffic information and vehicle motion data can be transmitted to ITS center via wireless communication technology. With the received traffic information like average velocity on each road in different time, and EV data like SOC, vehicle mass and motor characteristics, the ITS center is capable of calculating the EV accessible range and then send this information back to this EV. Therefore, high information storage and calculation capability are not necessary on the EV's side.

The framework of the mileage estimation method is shown in Fig. 1. First, a time-dependent stochastic traffic model is established to reflect the random and time-varying feature of the traffic system. And then, EV driving energy consumption needs to be estimated, and suitable (not detouring) routes connecting the origin and any other nodes in the map should also be selected. Due to the travelling speed on each road is subjected to time-dependent probability distribution, traditional route selection method like Dijkstra algorithm [11], Ford algorithm [12], Floyd algorithm [13] and A* algorithm [14, 15], are not applicable. Therefore, stochastic simulation based genetic algorithm is applied to choose suitable route and calculate energy consumption on each route. As the energy consumption results on each route is represented by a certain number of sampling results, the probability distribution of energy consumption on each route can be generated. Finally, the stochastic programming assessment standard is applied to estimate the accessible range. In this study, the generated accessible range is a random distribution result rather than a definite value, since the energy consumption on each route is not fixed value.

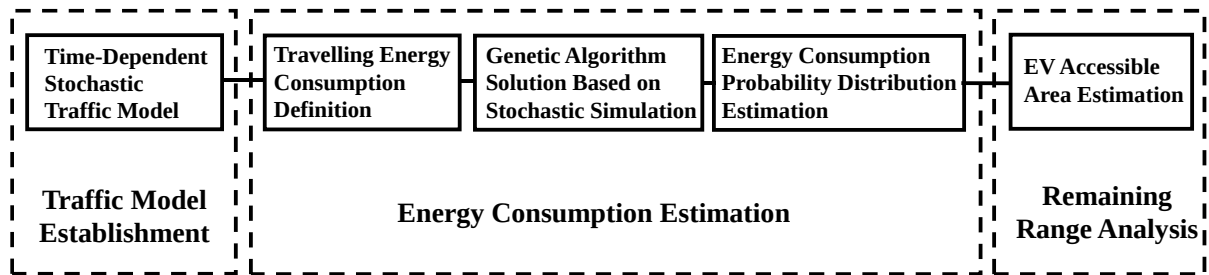


Figure 1: Estimation approach of the EV remaining range

3. Traffic Model

The real traffic environment is often in a dynamic and stochastic state, and the average velocity on each road is often submitted to various periodic (morning and evening peak) and aperiodic (weather, traffic accidents) effects. A time-dependent stochastic traffic model is developed here to describe the traffic environment [16, 17]. In this model, the average velocity on each road is a random variable subject to a time-changing

probability density function. This means that in one time period, the average velocity on one road obeys a certain distribution probability function, and as the time period changes, this average velocity obeys a different probability function. In this way, the traffic network has both the random and dynamic features.

The traffic model built here is $G = (V, \gamma, T, \phi)$, where $V = \{1, 2, \dots, n\}$ is the set of road nodes in the map, and $\gamma = \{(i, j) | i, j \in V\}$ is the set of directed paths in the map. δ is the minimum time interval and T is the set of time periods $\{t | t_0 + l\delta \leq t < t_0 + (l+1)\delta, l = 0, 1, 2, \dots\}$. ϕ is the set of the probability distributions of the average velocity and thus covers all possible velocity probability distributions of all roads in all time periods.

$$\phi = \bigcup_{(i,j) \in \gamma, t \in T} \phi_{ij,t} \quad (1)$$

Where $\phi_{ij,t}$ represents the probability distribution function of the average speed on road (i, j) at time t . If nodes i and j are not connected directly, $R_{ij} = \{r_{ij}^k : k = 1, 2, \dots, |R_{ij}|\}$ is defined as the route set connecting these nodes. r_{ij}^k is the k^{th} route connecting these nodes, and $r_{ij}^k = \{r_{ij}^k(z) : z = 1, 2, \dots, |r_{ij}^k| - 1\}$ represents that this route contains $|r_{ij}^k|$ nodes, and $r_{ij}^k(z)$ is the z^{th} path along route r_{ij}^k . $l(r_{ij}^k(z))$ is the length of path $r_{ij}^k(z)$, and $\alpha(r_{ij}^k(z))$ is the slope angle of path $r_{ij}^k(z)$.

4. Energy consumption estimation

4.1 Vehicle Energy Consumption

When the EV goes through the route r_{ij}^k , the driving energy consumption $E_D(r_{ij}^k)$ and travelling time $T_D(r_{ij}^k)$ are defined as follows:

$$E_D(r_{ij}^k) = \sum_{z=1}^{|r_{ij}^k|-1} E_D(r_{ij}^k(z)) \quad (2)$$

$$T_D(r_{ij}^k) = \sum_{z=1}^{|r_{ij}^k|-1} T_D(r_{ij}^k(z)) \quad (3)$$

Where $E_D(r_{ij}^k(z))$ and $T_D(r_{ij}^k(z))$ are the driving energy consumption and time consumption along the road $r_{ij}^k(z)$. Owing to the regenerative braking feature of EVs, braking energy can be restored to the battery when the EV runs downhill or decelerates. Hence, the energy efficiency function should be defined according to the driving situation[18].

$$\eta(x) = \begin{cases} \frac{x}{\eta_m \eta_d}, & x > 0 \\ \eta_{in} x, & x \leq 0 \end{cases} \quad (4)$$

Where the input variable x defines the form of this function, η_d is the efficiency of the final drive, η_m is the energy output efficiency of the electric motor, and η_{in} is the energy input efficiency due to regenerative braking. Thus, the energy and time consumption along path $r_{ij}^k(z)$ are defined as follows:

$$E_D(r_{ij}^k(z)) = \frac{1}{\eta_m \eta_d} [fG \cos \alpha(r_{ij}^k(z)) l(r_{ij}^k(z)) + \frac{C_D A \rho}{2} v(r_{ij}^k(z), t(r_{ij}^k(z)))^2 l(r_{ij}^k(z))] + \eta(G l(r_{ij}^k(z)) \sin \alpha(r_{ij}^k(z))) + \frac{1}{2} m \eta (v(r_{ij}^k(z+1), t(r_{ij}^k(z+1)))^2 - v(r_{ij}^k(z), t(r_{ij}^k(z)))^2) \quad (5)$$

$$T_D(r_{ij}^k(z)) = \frac{l(r_{ij}^k(z))}{v(r_{ij}^k(z), t(r_{ij}^k(z)))} \quad (6)$$

$$v(r_{ij}^k(z), t(r_{ij}^k(z))) \sim \phi_{r_{ij}^k(z), t_0 + l\delta} \quad (7)$$

$$t(r_{ij}^k(z+1)) = t(r_{ij}^k(z)) + T(r_{ij}^k(z)) \quad (8)$$

where

$$t_0 + l\delta \leq t(r_{ij}^k(z)) < t_0 + (l+1)\delta, \quad l = 0, 1, 2, \dots, \quad z = 1, 2, \dots, |r_{ij}^k| - 1$$

f is the rolling friction coefficient of the vehicle, m is the total mass value of the EV, G is the gravity of the EV, A is the frontal area of the vehicle, C_D is the air resistance coefficient, ρ is the air density. $v(r_{ij}^k(z), t(r_{ij}^k(z)))$ is the average velocity along path $r_{ij}^k(z)$ when the EV arrives at this path at time point $t(r_{ij}^k(z))$, and this velocity is subject to the average velocity probability distribution function $\phi_{r_{ij}^k(z), t_0 + l\delta}$. Therefore, $E_D(r_{ij}^k(z))$ is the total energy consumption $E(r_{ij}^k)$ on route $r_{ij}^k(z)$

4.2 Stochastic Simulation-based Genetic Algorithm

Because the average velocity $v(r_{ij}^k(z), t(r_{ij}^k(z)))$ on each path is subject to a time-variant probability distribution function, both the energy consumption $E_D(r_{ij}^k(z))$ and time consumption $T_D(r_{ij}^k(z))$ on a single route are random variables rather than a definite value. Besides, how to reasonably choose the routes connecting the EV's current position node i_0 and any other node j is also a problem. The route set connecting node i_0 and node j is defined as R_{i_0j} , and $r_{i_0j}^k \in R_{i_0j}$, $j \in V$. It is obvious that in this route set R_{i_0j} there are many detouring routes which are not representative, and the energy consumption of these detouring routes are unrealistically high. As a result, an optimization algorithm is utilized here to select reasonable (not detouring) routes within the R_{i_0j} and only these selected routes are further used in the range estimation procedure. The stochastic simulation-based genetic algorithm (GA) is utilized[19]. This method is particularly suitable for optimization problems with stochastic states. The structure of this algorithm is shown in Table. 1.

Table. 1 The algorithm structure of the stochastic simulation-based genetic algorithm

Stochastic simulation-based genetic algorithm (GA)

For all the destination node j in the map

Initialization

Random choose N_G routes from the route set R_{i_0j}

For iteration cycle $Iter=1, 2, \dots, N_{iter}$

Fitness calculation

For each route $k=1, 2, \dots, N_G$

For each calculation cycle $\omega=1, 2, \dots, N_S$

Calculate the energy consumption $E(r_{i_0j}^{k,\omega})$ of each route for N_S times.

end

end

Because the energy consumption $E(r_{i_0j}^k)$ is not a fixed value, the fitness value of each route $r_{i_0j}^k$ is defined as the average value of $E(r_{i_0j}^{k,\omega})$.

Selection

Combine the fitness value of each route $r_{i_0j}^k$ to build the roulette table, and randomly choose N_G routes from this table.

Crossover & Mutation

Set the crossover probability and mutation probability and change the node sequence of the routes $r_{i_0j}^k$, in order to explore new reasonable routes.

end

Sort the routes $r_{i_0j}^k$ according to the average energy consumption, and choose K ($K < N_G$) routes with minimum average energy consumption.

end

Therefore, the energy consumption results between the origin i_0 and all the other node j are obtained.

Besides the normal GA procedures, including initialization, selection, crossover and mutation, the major feature of this algorithm is the definition of the fitness value for each route. Due to the stochastic changing feature of the travelling velocity on each road, the energy consumption would not be a fixed value since the velocity on each road is not the same in different ω calculation turns. Therefore a proper way to represent the energy consumption is the average value.

After the whole optimization procedure between node i_0 and node j is accomplished, N_G routes connecting node i_0 and node j are selected by GA method, and then only K ($K < N_G$) routes with minimum energy consumption are chosen. There are two reasons for selecting K routes. First, at the beginning of EV range estimation, the route choice between node i_0 and node j is not determined, and choosing several routes connecting node i_0 and node j would represent the energy consumption comprehensively. Secondly, in the N_G routes, there are still detouring routes with high energy cost, which is unreasonable to be chosen to represent the energy consumption between node i_0 and node j . As a result, only K routes are selected to denote energy consumption between node i_0 and node j .

When the energy consumption of all the node j in the map have been evaluated, the optimization procedure is accomplished. This energy consumption data would be used as the foundation for range estimation.

4.3 Energy consumption probability distribution estimation

The energy consumption between node i_0 and node j is defined as random variable $E(i_0, j)$, and the results $E(r_{i_0j}^{\lambda, \omega})$, $\lambda = 1, 2, \dots, K$, $\omega = 1, 2, \dots, N_s$ are the sampling outcomes of this probability distribution of $E(i_0, j)$. In order to use the $E(r_{i_0j}^{\lambda, \omega})$ data to estimate the energy consumption probability distribution, the Parzen Window function is used[20]:

$$p_{i_0j}^{E,T}(x) = \frac{1}{KN_s} \sum_{q=1}^{KN_s} \frac{1}{V} \varphi\left(\frac{x - x_{i_0j}^q}{h}\right) \quad (9)$$

$$\varphi([u_1, u_2, \dots, u_d]^T) = \begin{cases} 1 & \text{if } |u_i| \leq \frac{1}{2}, i = 1, 2, \dots, d \\ 0 & \text{else} \end{cases} \quad (10)$$

$$V = h^d \quad (11)$$

$$x_{i_0j}^q = (E(r_{i_0j}^{\lambda, \omega}), T(r_{i_0j}^{\lambda, \omega})) \quad (12)$$

where

$$\omega = 1, 2, \dots, N_s, \quad \lambda = 1, 2, \dots, K, \quad q = 1, 2, \dots, K \times N_s$$

For each destination node j , the number of energy consumption data is $K \times N_s$, since there are K routes and N_s energy consumption data for each route. We define $p_{i_0j}^{E,T}(x)$ as the joint probability distribution estimation of energy and time consumption.

4.4 Remaining range analysis strategy

Due to the stochastic time-changing traffic model, the energy consumption $E(i_0, j)$ between i_0 and j is a random variable subject to $p_{i_0j}^E(x)$. Here we use the stochastic programming models to calculate the reachable probability of node j . The model we adopt here is the expectation value model. The expectation model use the average value of random variable to represent the random distribution of energy consumption, and further to predict the remaining range. The remaining battery energy E_B and the average value of $E(i_0, j)$ is compared with each other. If the remaining battery energy is bigger than the average value of $E(i_0, j)$, then

node j is considered to be reachable. All the destination nodes in the map would go through this procedure, and the accessible range of this EV can be obtained.

5. Simulation Design

To verify the performance of the proposed range estimation method, a simulation model and analysis strategy are set up. The historical driving information based range estimation method and present traffic information based range estimation are also selected for comparison. Basic parameters about the EV and simulation parameter are provided in Table 2.

Table 2: Simulation Parameters

<i>Parameters</i>	<i>Value</i>	<i>Units</i>	<i>Notes</i>
E_B	8	KWh	Battery energy
m	1100	kg	Vehicle mass
ρ	1.2258	Ns^2m^{-4}	Air density
C_D	0.31	-	Air resistance coefficient
A	2.15	m^2	Frontal area
δ	5	Minutes	Minimum time interval
K	5	-	
N_s	20	-	

5.1 Simulation Model

As shown in Figure 2, a $150\text{km} \times 150\text{km}$ road map is established and this map has 400 nodes. The red point is the start point. The velocity data on each road is based on the history traffic data in [21]. This data set have been collected from the real velocity data of the 4th ring road in Beijing, and was sampled every 5 minutes, totally 288 data points per day over two month. According to [21], the original data have been verified to be close to a time-variant normal distribution. Therefore, in the simulation model, the average velocity of each road is subject to this time-variant normal distribution.

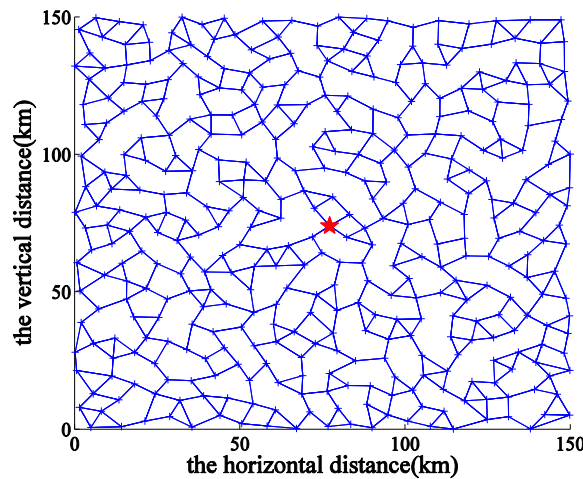


Figure 2. Stochastic time-dependent traffic simulation model

5.2 Result Analysis Strategy

To verify the effectiveness of the range estimation methods, an analysis criteria is established in Fig. 3. The coincidence area, underestimated area and the overestimated area are defined.

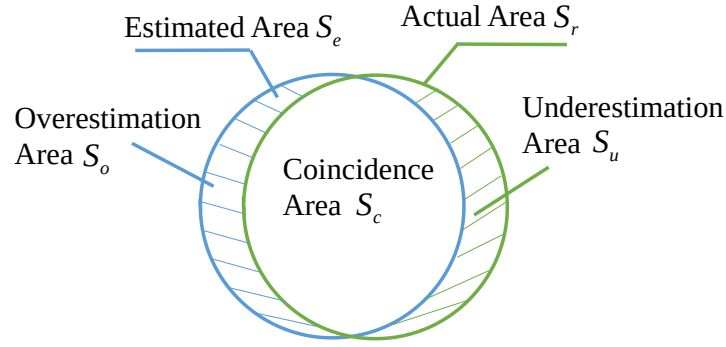


Figure 3. Appraisal strategy for the range estimation results

The evaluation standard are defined as coincidence rate λ_c , underestimated rate λ_u and overestimated rate λ_o . Therefore, for a good estimation results the coincidence rate λ_c should be high and the sum of λ_u and λ_o should be low. A comprehensive evaluation index λ_{index} is defined.

$$\begin{aligned}\lambda_c &= \frac{S_c}{S_r} \times 100\% \\ \lambda_u &= \frac{S_u}{S_r} \times 100\% \\ \lambda_o &= \frac{S_o}{S_r} \times 100\% \\ \lambda_{index} &= \lambda_c - \lambda_u - \lambda_o\end{aligned}\tag{13}$$

6. Simulation results and analysis

Since the simulation model and analysis method are established, simulation analysis are implemented.

6.1 Range estimation comparison between a static deterministic traffic environment and a stochastic time-dependent traffic environment

The main feature of the proposed method is the application of the stochastic time-dependent traffic model. The comparison have been made between the proposed method and the range estimation method based on the present traffic information, shown in Fig. 4.

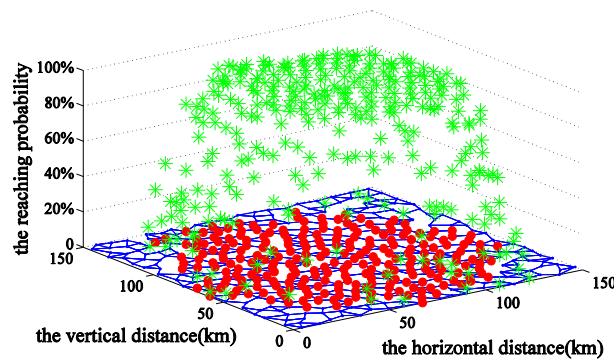


Figure 4. Range estimation comparison in different traffic environment model

In Fig. 4, the departure time is 8:00 am, and red points represent the accessible area based on the present traffic information, and the green points show the reachable area based on probabilistic range estimation method. The result of the red points is a static deterministic reachable area, since the unchangeable velocity on each road in the map lead to the fixed energy consumption on the route, therefore the reachability of all

the node in the map is clear. When it comes to the green points, the reachability of each node is a probability value, since the velocity on each road is a random variable subjected to a dynamic stochastic distribution.

6.2 Comparison with different estimation methods

The range estimation methods based on the past driving information and present traffic information are selected to compare with the proposed estimation method. The first method is based on historical driving data. In each simulation cycle, a route (the length is less than 10km) connecting the origin is randomly chosen to represent the past driving history. Therefore before each simulation cycle, a distance-energy ratio can be calculated and EV range can be estimated. Due to the stochastic changing feature of the traffic system, the energy-distance ratio and remaining range estimation are different in each simulation cycle.

For the second comparison method, the traffic data of all road links at the departure time are utilized. This data set is applied to calculate the energy consumption along each road and to estimate the remaining mileage. Due to the changing feature of the traffic model, even at the same departure time, the traffic data would be different in each simulation cycle, and 100 simulation cycles at each departure time are carried out.

To verify the performance of different methods, the real accessible area is also simulated. In each simulation cycle, in order to reach a node in the map, one suitable and reasonable route selected by the GA is randomly chosen, and the energy consumption is calculated under the stochastic time-dependent traffic model. If the battery energy is greater than the energy consumption, this node is considered to be reachable in this simulation cycle. Through this procedure, the real accessible area of the electric vehicle is obtained. The actual accessible area is generated 100 times for each departure time to ensure a comprehensive comparison.

The estimation method based on past driving data (P), the estimation method based on the present traffic data (R) and the proposed expectation estimation method (E) based on dynamic stochastic traffic information are compared. We use C,U,O to represent $\lambda_c, \lambda_u, \lambda_o$, respectively. The simulation results are as in Fig. 5.

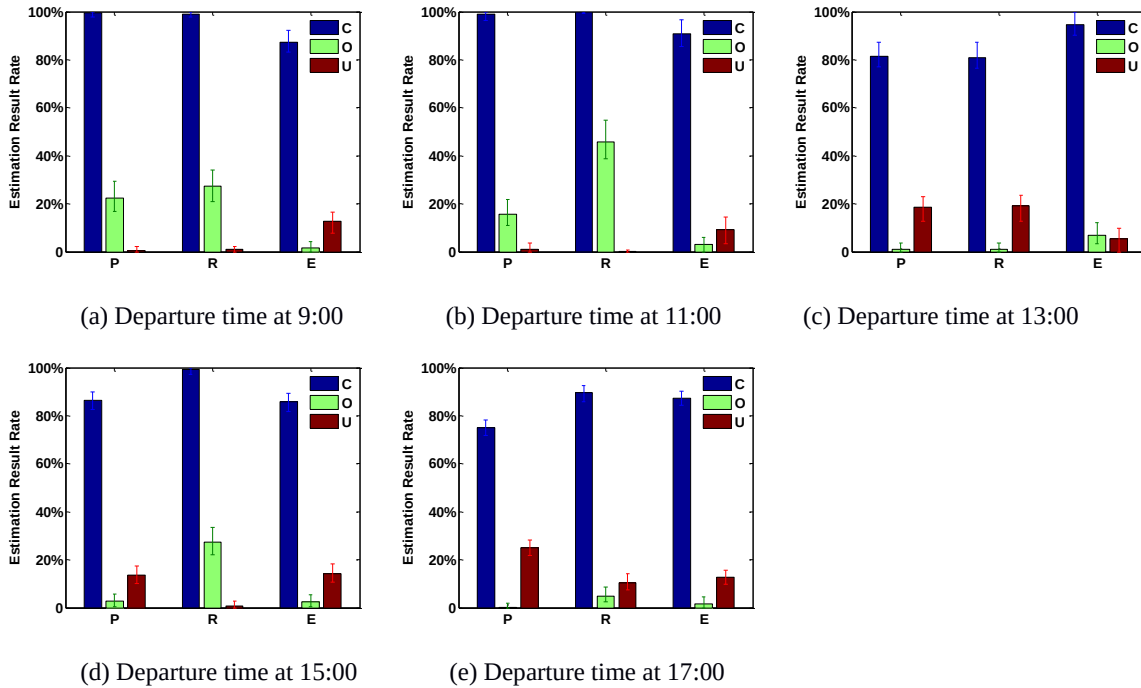


Figure. 5. Comparative simulation experiment results from 9:00 to 17:00 in one day

A good range estimation method is the one that provides a high coincidence rate while keeping the overestimated rate and underestimated rate as low as possible. As observed from Fig. 5, the estimation results based on past driving data and present-time traffic information are both unsatisfactory, because under some circumstances the coincidence rate of these two methods are below that of the expectation model, such as at the departure time of 13:00. At other departure times, although the coincidence rates are excellent, the

overestimation rate or the underestimation rate are too high, leading the estimation results to be unrealistic, as can be found at the departure times at 9:00, 11:00 and 15:00.

For the expectation model, the estimation results are acceptable since the coincidence rates are reasonably high and the overestimated and underestimated rates are relatively low. Moreover, a good range estimation method should be accurate consistently, no matter when the vehicle leaves the origin point, to enhance the driver's confidence in this estimation method. The comparison of comprehensive estimation index are calculated from departure time 9 o'clock to departure time 17 o'clock, as shown in Fig 6.

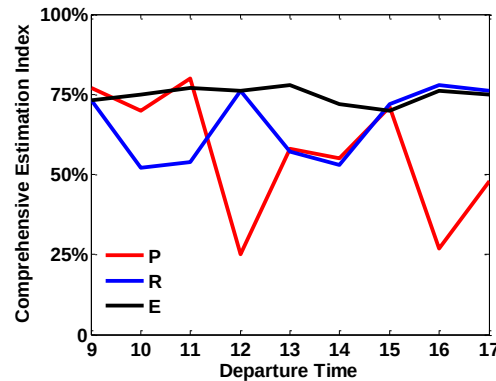


Figure 6. The consistency comparison of different methods

From Fig. 6, the comprehensive estimation index of different methods are compared, and it is obvious that λ_{index} of the expectation method holds the most stable estimation consistency as well as a good comprehensive estimation performance.

7. Conclusions

In this paper, a range estimation method based on the stochastic time-dependent traffic information is proposed. This method treats the travelling velocity along each route to be a time-variant probability distribution, and then predicts the reachable area for the electric vehicle. In this way, the time-dependent stochastic changing feature of the traffic model have been taken into consideration. According to the results of multiple simulation experiments, the performance of the proposed range estimation method exceeds that of the other two traditional methods in most scenarios, and consistent accuracy of the estimation results can be realized.

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