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Network traffic flow evolution with battery electric vehicles and conventional gasoline vehicles

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Abstract: In order to investigate the effect of the use of battery electric vehicles on traffic dynamics, the valid paths of electric battery vehicles are defined and a check-based method is proposed to obtain them. Then, assuming that travelers only focus on their past travel experience, a day-to-day traffic assignment model is established based on reinforcement learning and bounded rationality. In the proposed model, the Bush-Mosteller model, a reinforcement learning model, is modified to calculate path choice probability according to bounded rationality. The modified model updates the path choice probability only if the gap between expected travel time and perceived travel time is beyond the cognitive threshold. Numerical experiments validate the effectiveness of the model and show that traffic flows can converge to the equilibrium in any case of cognitive thresholds and penetration rates of battery electric vehicles. The cognitive threshold has a positive influence on the variation of traffic flows while it has a negative influence on the differences between traffic flows. The adaptation of battery electric vehicles leads to the poor performance of the traffic system.

Key words: battery electric vehicles; constrained path; reinforcement learning; bounded rationality; traffic dynamics

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Day-to-day traffic assignment models that aim to capture the evolutionary process of the traffic system can be used not only to evaluate traffic management measures but also to provide information about dynamic traffic flow for dynamic navigation[1]. Due to their usefulness, these models and traffic dynamics have been widely studied in the past few decades. However, to the best of our knowledge, these studies assumed that travelers only use conventional gasoline vehicles (CGVs).

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Battery electric vehicles (BEVs) have enjoyed a fast-growing adoption in recent years, thanks to the concern about climate change, the advancement of battery technologies and expeditiously rising prices of crude oil[2]. However, the limited driving range of BEVs and insufficient charging infrastructure cause drivers to fear that batteries will run out of power on the path that is normally referred to as range anxiety in Ref. [3]. Psychology inevitably affects BEV drivers' travel choices, which might result in different traffic dynamics. Therefore, this paper focuses on analyzing day-to-day traffic dynamics with battery electric vehicles and conventional gasoline vehicles and examining how the use of BEVs influences traffic dynamics. To complete this, the day-to-day traffic assignment model needs to be first established.

According to the levels of aggregation, day-to-day traffic assignment models can be divided into two categories: macroscopic models based on the flow swapping rule and microscopic models based on path choice behavior. The macroscopic models focus on how traffic flows switch, which always describes traffic flow on a path on a certain day as the function of the network state of the previous day. Classic models have a proportional switching adjustment[4], tatonnement process[5] and projected dynamical system[6]. The microscopic models put the emphasis on how the individual adjusts his/her path choice based on information or experience. For example, Nakayama et al. [7] took into account the limitation of drivers' cognitive abilities in their path choice model and examined the dynamic natures of the traffic system. Zhang and He[8] established a path choice model based on the prospect theory. Rossetti and Liu[9] incorporated mental attitudes in the model and investigated how pre-trip information has an impact on the evolution of the traffic system. Compared to the macroscopic models, these microscopic models can incorporate a variety of factors that affect the evolution of the traffic system and thus better represent the dynamics of the traffic system[10]. Therefore, we decided to establish our day-to-day traffic assignment model based on path choice behavior from a microscopic perspective.

This study makes the following specific contributions. First, the valid paths for battery electric vehicles are defined and a method of obtaining them is given. Secondly, the proposed day-to-day traffic assignment model incorporates travelers' bounded rationality that travelers cannot distinguish minor differences between path attractiveness. Finally, we examine the effects of the use of battery electric vehicles and bounded rationality on the dynamic natures of traffic flow by numerical experiments.

1 Valid Path

The first problem that needs to be dealt with in establishing the day-to-day assignment model is to determine valid paths that can be chosen by travelers. For CGVs, a valid path between an origin-destination (OD) pair consists of valid links and each valid link is a link of which its end is closer to the destination than its start[11]. The distance between two nodes is calculated as the Euclidean distance. Based on the definition, the valid paths between each OD pair for CGVs can be quickly obtained by the following steps:

Step 1 Create a partial path set B and a whole path set F; then put the origin node into B and set it as the current path.

Step 2 Search the new nodes that directly link to the last node of the current path and these must be closer to the destination node than the last node of the current path based on the Euclidean distance. The current path is then replicated as many times as the number of the new nodes minus one and the tails of the current path and the replicated paths are, respectively, added into one of the new nodes. Then, the replicated paths are added into the partial path set B.

Step 3 Transfer the current path from B into F and go to Step 4 if the last node in the current path is the destination; otherwise, go to Step 2.

Step 4 Stop if B is empty; otherwise, select a path from B as the current path and go to Step 2.

For BEVs, the limited battery capacity limits its driving range[12]. However, the charging stations in the traffic network can supplement fuel for BEVs. Based on these features, we definite the valid path of BEVs as follows: A valid path between an OD pair for battery electric vehicles consists of valid links and the rest of its driving range at any node that is not less than 0. The definition of the valid link is the same as that of CGVs. The constraint can be expressed in a mathematical equation as follows:

$$r_j \geqslant 0 \qquad \forall j \in \overline{N} \tag{1}$$

and the remaining driving range is given as

$$r_j = r_i - L_{ij} + (D_{\max} - r_i) Y_i \qquad \forall (i, j) \in \overline{A} \tag{2}$$

where r_j is the remaining driving range when the battery electric vehicle arrives at node j; $\overline{N}$ is the set of nodes that belong to a valid path; L_{ij} is the length of valid link (i, j); $\overline{A}$ is the set of valid links that belong to a valid path; $D_{\max}$ represents the maximum driving range of a battery electric vehicle with a full charge; Y_i indicates whether node i is a charging station or not. If yes, its value is 1; otherwise, its value is 0.

Based on the definition of the valid path of BEVs, we can infer that the valid path of the BEVs between an OD pair must be that of the CGVs. Also, the valid paths of CGVs between each OD pair in a given traffic network can be quickly obtained by the above procedures. Therefore, we proposed a check-based method to obtain the valid path of the BEVs. Its process is described in the following:

Step 1 Calculate its remaining driving range at each node according to formulae (1) and (2) for a valid path of CGVs between an OD pair;

Step 2 Record the valid path if the remaining driving range at each node is no less than 0;

Step 3 Repeat Steps 1 and 2 until all the valid paths of the CGVs between the OD pair are checked.

2 Day-to-Day Traffic Assignment Model

2.1 Path adjustment process

Travelers' path choice is a continuous adjustment process. When a traveler finishes a trip in the traffic network, he/she will be able to learn the travel cost of the chosen path and form an opinion about the state of the path. Furthermore, he/she will infer the state of the whole traffic network based on the experience and predict the travel cost the next day. On a certain day, the difference between the expected travel cost and experienced travel cost contributes to his/her utility for the choice and motivates him/her to adjust the path choice probability, which is exactly the reason why the traffic dynamics exists. Fig. 1 shows the adjustment process. As the main travel cost for travelers is time, the travel cost is replaced with the travel time in Fig. 1 and in the rest of the paper.

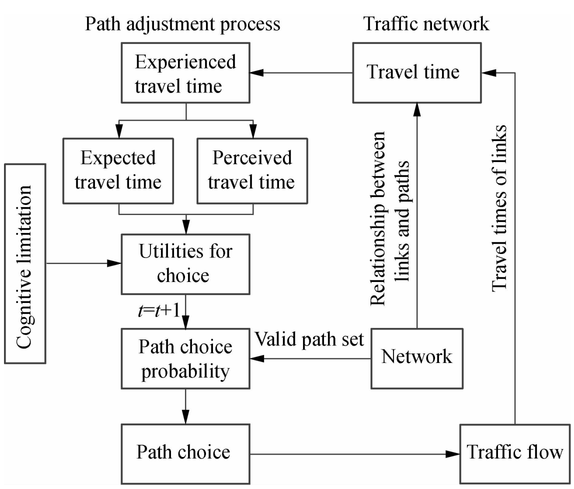


Fig. 1 Path adjustment process

2.2 Path adjustment model

The above description of the path adjustment process shows that travelers' path choices depend on the choice probabilities of the alternatives. The probability is continuously updated based on the difference between expected travel time and perceived travel time. We clearly elaborate on the three key elements in the next section.

2.2.1 Parameters

We represent a traffic network as a directed graph $G=(N, A)$, where N is a node set and A is a link set. Among nodes, there are origin nodes O, destination nodes D and charging nodes C. There are several OD pairs denoted as W in the traffic network. An OD demand, $d_w(w \in W)$, is equal to the sum of the number of the drivers of CGVs and BEVs. The valid paths of BEVs between an OD pair are denoted as R_w while the valid paths of CGVs are denoted as $R'_w(R'_w \in R_w)$. Let $f_k^{wt}(k \in R_w)$ be the traffic flow on path k between OD pair w and $v_a^t(a \in A)$ be traffic flow on link a on day t, respectively. The travel times of path k between OD pair w and link a on day t are, respectively, represented as T_k^{wt} and H_a^t. δ_{ak} is the link-path index. Let δ_{ak} be equal to 1 if link a belongs to path k and to 0 otherwise. M_i^w denotes the vehicle type that traveler i $(i \in d_w)$ uses. M_i^w equals 1 if traveler i uses the battery electric vehicle and 0 if he/she uses the conventional gasoline vehicle.

2.2.2 Expected travel time

With the accumulation of travel experience, a traveler will further know the state of the whole traffic network little by little and subsequently update his/her expected travel time. Due to the limitation of human being's memory, the experience obtained at different times has a different impact on his/her cognition. As the recently obtained experience can be clearly memorized, its impact should be more significant compared to the older one. Therefore, we give a greater weight value to the recently experienced travel time when calculating expected travel time. Assuming that the weight exponentially weakens over time, the travel time that the traveler expects the next day can be written as

$$E_i^{t+1} = \frac{\sum_{n=1}^{t} \psi^{t-n+1} h_i^n}{\sum_{n=1}^{t} \psi^{t-n+1}} \tag{3}$$

where E_i^{t+1} is the expected travel time of traveler i on day $t+1$; ψ is a constant that represents the extent of memory decay; h_i^n is the travel time that traveler i experiences on day n.

Although travelers do not have any experience on day 1, he/she can know the topology of the traffic network. Therefore, we set the expected travel time of travelers on day 1 as the minimal free-flow travel time of all potentially chosen paths.

2.2.3 Perceived travel time

Without traffic information, the only way for the traveler to acquire the path travel time is to travel within the traffic network. Therefore, the path travel time that the traveler perceives totally depends on his/her experienced path travel time.

$$g_{ik}^t = \frac{\sum_{n=1}^{t} \psi^{t-n+1} \xi_{ik}^n h_i^n}{\sum_{n=1}^{t} \psi^{t-n+1} \xi_{ik}^n} \qquad \forall k \in M_i^w R_w + (1-M_i^w) R'_w \tag{4}$$

where g_{ik}^t is the perceived travel time of path k of traveler i on day t; ψ and h_i^n are the same as mentioned above; ξ_{ik}^n indicates the path choice of traveler i on day n. ξ_{ik}^n equals 1 if traveler i chooses path k on day n and 0 otherwise.

As the traveler just travels one path once, the following constraint should be met.

$$\sum_{k \in M_i^w P_w + (1-M_i^w) P'_w} \xi_{ik}^n = 1 \tag{5}$$

2.2.4 Path choice probability

A traveler finishes a trip and grasps the real travel time of his/her chosen path. Then, he/she will evaluate his/her choice and update the path choice probabilities. If his/her expected travel time is greater than the experienced travel time, he/she will obtain a positive utility from the choice and increase the choice probability of the chosen path; otherwise, he/she will obtain a negative utility from the choice and reduce the probability, which matches well with reinforcement learning[13]. In addition, due to the bounded rationality of the human beings that are not able to recognize the minor difference, the discrepancy between the expected travel time and the experienced travel time that can motivate the traveler to adjust the path choice probability must be beyond a certain range. Therefore, according to the bounded rationality theory, we modified the Bush-Mosteller model, a reinforcement learning model, as our path choice probability model. It is displayed as

$$P_{ik}^{t+1} = \begin{cases} P_{ik}^t + (1-P_{ik}^t) l S_i^t & S_i^t \geqslant 0 \\ P_{ik}^t + P_{ik}^t l S_i^t & S_i^t < 0 \end{cases}$$

$$\forall k \in M_i^w R_w + (1-M_i^w) R'_w, \ \text{if } \xi_{ik}^t = 1 \tag{6}$$

$$P_{ik}^{t+1} = \begin{cases} P_{ik}^t - P_{ik}^t l S_i^t & S_i^t \geqslant 0 \\ P_{ik}^t + \dfrac{P_{ik}^t l S_i^t \sum_{k \in M_i^w R_w + (1-M_i^w) R'_w} \xi_{ik}^t P_{ik}^t}{\left(1 - \sum_{k \in M_i^w R_w + (1-M_i^w) R'_w} \xi_{ik}^t P_{ik}^t\right)} & S_i^t < 0 \end{cases}$$

$$\forall k \in M_i^w R_w + (1-M_i^w) R'_w, \ \text{if } \xi_{ik}^t \neq 1 \tag{7}$$

$$S_i^t = \begin{cases} \dfrac{E_i^t - \sum_{k \in M_i^w R_w + (1-M_i^w) R'_w} \xi_{ik}^t g_{ik}^t}{\max_{k \in M_i^w R_w + (1-M_i^w) R'_w} (E_i^t - g_{ik}^t)} & E_i^t - g_{ik}^t - \theta E_i^t > 0 \\ 0 & |E_i^t - g_{ik}^t| \leqslant \theta E_i^t \\ \dfrac{E_i^t - \sum_{k \in M_i^w R_w + (1-M_i^w) R'_w} \xi_{ik}^t g_{ik}^t}{\min_{k \in M_i^w R_w + (1-M_i^w) R'_w} (E_i^t - g_{ik}^t)} & E_i^t - g_{ik}^t + \theta E_i^t > 0 \end{cases} \tag{8}$$

where P_{ik}^{t+1} is the probability that traveler i chooses path k on day $t+1$; l is a constant that represents the learning efficiency; S_i^t is the utility of traveler i for the choice on day t; θ is a proportion that reflects travelers' cognitive thresholds; and the rest is the same as the above.

Without loss of generality, travelers' cognitive thresholds are set to be the same in our model. Of course, the model can be extended to describe heterogeneous cognitive limitation among travelers by simple modification. For example, the cognitive threshold is related to travelers and is set to be θ_i. The cognitive threshold is mainly presented in two ways in literature: a constant or a fixed proportion[14]. A fixed proportion is adopted here since many empirical studies show that the indifference band expands with the cognitive base number.

2.3 Traffic system

The traffic system should meet the following constraints every day.

$$d_w = \sum_{k \in R_w} f_k^{wt} \qquad \forall w \in W \tag{9}$$

$$v_a^t = \sum_{w \in W} \sum_{k \in R_w} \delta_{ak} f_k^{wt} \qquad \forall a \in A \tag{10}$$

$$T_k^{wt} = \sum_{a \in A} \delta_{ak} H_a^t \qquad \forall k \in R_w, w \in W \tag{11}$$

Eq. (9) demonstrates that an OD demand is distributed over all the paths between the OD pair; Eq. (10) indicates that the traffic flow on a link is equivalent to the sum of the traffic flow of all paths that the link belongs to; and Eq. (11) constrains that the travel time of a path is equal to the sum of travel times of all links that the path consists of.

3 Numerical Experiments and Analyses

Due to the complexity of the proposed day-to-day traffic assignment model, the equilibrium path choice probability cannot be analytically solved. Therefore, we analyze the dynamic nature of the proposed system by numerical examples in this section. In the experiments, the learning efficiency and memory decay of travelers are set to be 0.3 and 1, respectively. The evolution day is set to be 1 500.

3.1 Network characteristics

The Nguyen-Dupuis network shown in Fig. 2 is used here to analyze the traffic dynamics with conventional gasoline and battery electric vehicles. The network consists of 13 nodes and 4 OD pairs. Among the nodes, node 5 and node 10 are charging stations. The link free-flow travel time and capacity are from Wei et al[13]. The link distance is assumed to be 1.5 times of its free-flow travel time[2]. The BPR function is adopted to calculate the link travel time[13]. The maximum driving range of the BEVs with full charge is set to be 40 so the BEVs need to recharge during the trip.

The OD demands of Zhang et al. [15] are adopted here, displayed in Fig. 2. As the adopted network is small and does not have coordinate information, we find all paths between an OD pair as the alternatives of CGVs instead of the valid paths. It is noted that the valid path should be used in a real network. Then, the valid paths of BEVs in Tab. 1 are obtained by the proposed method here.

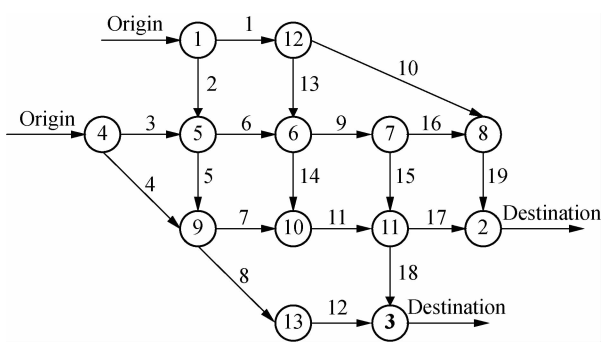


Fig. 2 Nguyen-Dupuis network

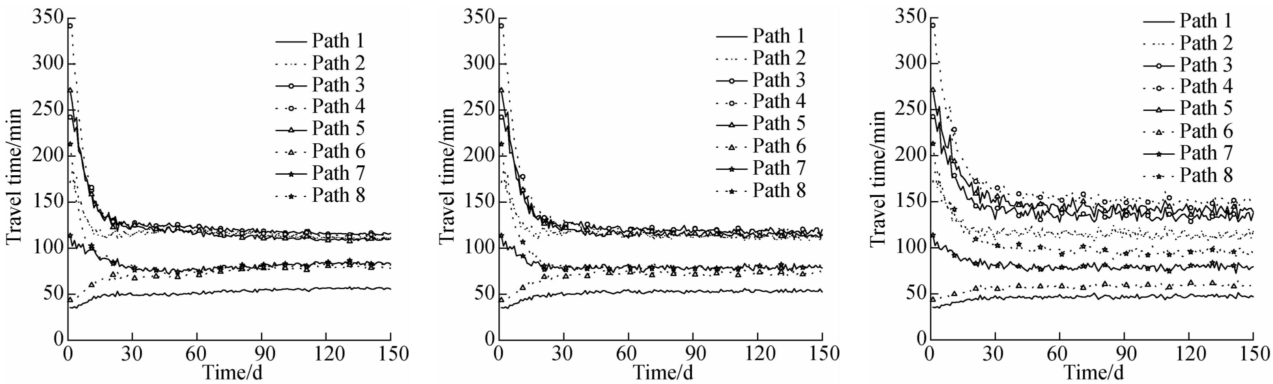
Tab. 1 Valid paths

OD pair	(1, 2)	(1, 3)	(4, 2)	(4, 3)
Valid paths of CGVs	1(1-10-19)	1(2-5-8-12)	1(4-7-11-17)	1(4-8-12)
	2(2-6-9-16-19)	2(2-6-9-15-18)	2(3-6-9-16-19)	2(4-7-11-18)
	3(2-6-9-15-17)	3(2-6-14-11-18)	3(3-6-9-15-17)	3(3-5-8-12)
	4(2-6-14-11-17)	4(2-5-7-11-18)	4(3-6-14-11-17)	4(3-6-9-15-18)
	5(2-5-7-11-17)	5(1-13-9-15-18)	5(3-5-7-11-17)	5(3-6-14-11-18)
	6(1-13-9-16-19)	6(1-13-14-11-18)		6(3-5-7-11-18)
	7(1-13-9-15-17)			
	8(1-13-14-11-17)			
Valid paths of BEVs	2(2-6-9-16-19)	2(2-6-9-15-18)	1(4-7-11-17)	2(4-7-11-18)
	4(3-6-9-15-18)	3(2-6-9-15-17)	3(2-6-14-11-18)	2(3-6-9-16-19)
	5(3-6-14-11-18)	4(2-6-14-11-17)	4(2-5-7-11-18)	3(3-6-9-15-17)
	6(3-5-7-11-18)	5(2-5-7-11-17)		4(3-6-14-11-17)
				5(3-5-7-11-17)

3.2 Impact of cognitive threshold

Most studies on traffic dynamics assumed that travelers are perfectly rational. In contrast to them, travelers are boundedly rational here, which is also validated by many empirical studies. We investigated whether the bounded rationality of travelers has an impact on traffic dynamics and what the impact is. Therefore, we conducted a series of experiments with different cognitive thresholds. The results are displayed in Fig. 3.

We can clearly observe from Fig. 3 that path travel time all quickly converges to the equilibrium under different cognitive thresholds. However, the variation of travel time varies with the cognitive threshold. When the cognitive threshold increases from 0% to 40%, each line in the figure disperses wider, which means that the path travel time fluctuates more. This phenomenon demonstrates that the cognitive threshold has a positive influence on the variation of traffic flow. This can be explained by the fact that with the increase in the cognitive threshold, a wider travel time range is the same for travelers.



(a) (b) (c)

Fig. 3 Travel time evolution with different cognitive thresholds. (a) $\theta=0$; (b) $\theta=0.2$; (c) $\theta=0.4$

Tab. 2 shows the average travel time and traffic flow of each path between OD pair 1-2 during the last 100 days. The valid paths of BEVs are path 2, path 3, path 4 and path 5. When the traffic flow reaches the equilibrium, the paths that travelers choose are path 2, path 3, path 4 and path 5, which is in descending order. On the contrary, the travel times of these paths are in ascending order. This means that the shorter the path travel time, the larger the number of travelers who will choose it, which is consistent with real traffic flow distribution. In other words, the day-to-day traffic assignment model proposed here is correct. In addition, it can be observed from Tab. 2 that the differences between the number of travelers choosing path 2, path 3, path 4 and path 5 become smaller with the increase in the cognitive threshold. The reason behind it is that a larger cognitive threshold represents a smaller sensitivity to the difference.

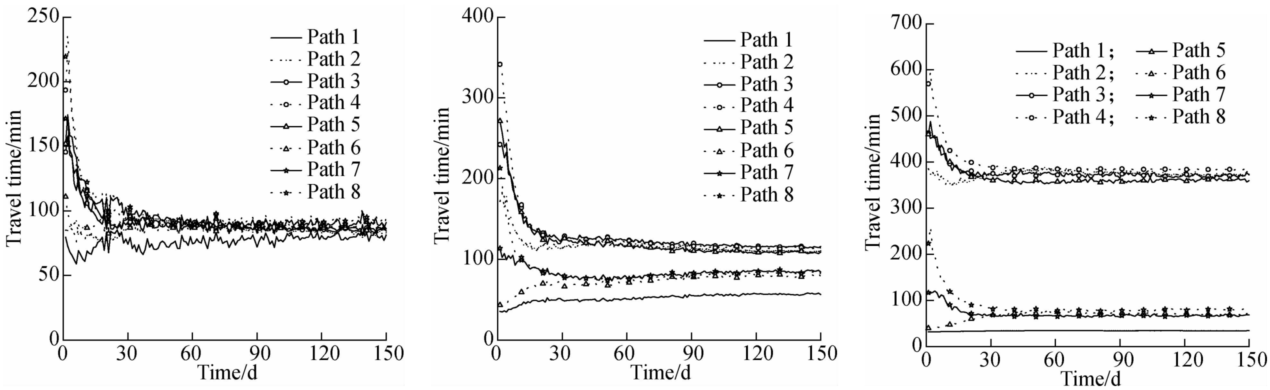
Tab. 2 Equilibrium traffic flows and travel time with different cognitive thresholds

Path between OD pair 1-2	$\theta=0$		$\theta=0.2$		$\theta=0.4$	
	Traffic flow/ $(\mathrm{veh}\cdot\mathrm{h}^{-1})$	Travel time/min	Traffic flow/ $(\mathrm{veh}\cdot\mathrm{h}^{-1})$	Travel time/min	Traffic flow/ $(\mathrm{veh}\cdot\mathrm{h}^{-1})$	Travel time/min
1	129.98	55.14	156.64	54.14	126.14	49.23
2	154.99	110.30	159.96	110.06	77.08	109.98
3	15.00	114.41	17.68	116.26	42.58	129.32
4	6.00	115.78	4.83	117.32	33.37	143.87
5	25.01	112.34	17.66	113.16	47.62	136.61
6	60.01	76.09	37.53	71.40	72.52	61.49
7	6.01	80.21	5.66	77.60	0.53	80.84
8	3.00	81.58	0.04	78.66	0.16	95.38

3.3 Impact of penetration rate of battery electric vehicles

We also analyzed the impact of the penetration rate of battery electric vehicles on the dynamic natures of the traffic system. To this end, we conduct a group of numerical experiments using different penetration rates of BEVs (r). Fig. 4 show the results.

Fig. 4 clearly shows that traffic systems with different penetration rates of BEVs are all able to reach their equilibriums, but their equilibrium states are different. When the penetration rate of BEVs is 0%, which means that all the travelers use conventional gasoline vehicles, the travel time of all travelers is roughly the same in the equilibrium state. However, when some travelers start to use battery electric vehicles, there are three equilibrium travel times. Among them, the largest equilibrium travel time is the convergence of the travel time of the valid paths of the BEVs, the smallest one is the minimal travel time, and the rest of them is the free-flow travel time of the rest of paths. The reason why the equilibrium travel time of valid paths of BEVs is the longest is that the limited driving range of BEVs and the scarcity of charging stations make potentially chosen paths fewer and longer.



(a) (b) (c)

Fig. 4 Travel time evolution with different penetration rates of battery electric vehicles (BEVs). (a) $r=0$; (b) $r=0.5$; (c) $r=1$

We report the average traffic flows and travel time of the paths between O-D pair 1-2 from day 1 401 to day 1 500 and the total travel time with different penetration rates of BEVs in Tab. 3. The total travel time increases from 32 644. 6 to 147 550. 1 when the penetration rate changes from 0% to 100%. This data shows that the efficiency of the traffic system becomes significantly lower as the penetration rate of BEV increases. In other words, the use of battery electric vehicles leads to the poor performance of the traffic system, which can be partly attributed to fewer alternative paths for BEVs. The fewer the alternatives, the more travelers who will choose the same path, leading to longer travel time. Another reason might lie in the shortage of charging stations. The shortage of charging stations leads to the fact that BEVs must travel on a longer path with a charging station to complete a trip. Therefore, it is necessary to build sufficient charging stations in the traffic network when travelers start to use battery electric vehicles. This approach will avoid the need for a detour of BEVs for recharging, thus improving the performance of the traffic system and successfully saving energy resources.

Tab. 3 Equilibrium traffic flows and travel time with different penetration rates of BEVs

Path between OD pair 1-2	$r=0$		$r=0.5$		$r=1$	
	Traffic flow/ (veh · h^{-1})	Travel time/min	Traffic flow/ (veh · h^{-1})	Travel time/min	Traffic flow/ (veh · h^{-1})	Travel time/min
1	332.03	81.18	134.99	54.83	0	33.98
2	56.78	83.06	156.74	110.97	349.37	369.15
3	0.28	85.10	11.93	115.73	19.60	369.25
4	0.14	87.82	7.11	116.47	2.08	383.23
5	0.19	86.32	25.22	112.22	28.95	364.33
6	10.29	87.13	55.00	75.14	0	68.01
7	0.18	89.17	7.24	79.90	0	68.12
8	0.11	91.89	1.77	80.64	0	82.10
Total travel time/min	32 644.68		34 687.15		14 7550.1	

4 Conclusions

1) The cognitive threshold and the penetration rate of BEVs have no influence on the convergency of traffic flows.

2) A large cognitive threshold can lead to small differences between traffic flows and their intensive variations since the sensitivity of travelers for differences has a negative relationship with the cognitive threshold.

3) The efficiency of the traffic system becomes low as the penetration rate of battery electric vehicles increases. One reason is that the limited driving range constraints potentially used paths, thus leading to the concentration of travelers. The other possible reason is that the shortage of charging stations forces drivers of battery electric vehicles to detour for recharging. Therefore, it is necessary to build sufficient charging stations in a traffic network in order to improve the performance of the traffic system and successfully save energy sources.

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混合纯电动汽车与传统汽油车的网络交通流演化

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摘要: 为了研究纯电动汽车使用对交通流演化特性的影响,定义了纯电动汽车的有效路径,提出了一种获得纯电动汽车有效路径的检查依据方法. 假设出行者仅能获得出行经验信息,依据强化学习和有限理性理论建立了出行者逐日路径选择模型. 在所提出的模型中,依据有限理性理论改进了 Bush-Mosteller 强化学习模型计算路径选择概率. 改进的模型只在出行者的期望出行时间与认知出行时间差异高于认知阈值时,才更新路径的选择概率. 数值实验证实了模型的有效性,表明交通流不受出行者认知阈值和纯电动车渗透率的影响总能汇聚到均衡状态;交通流的波动与出行者认知阈值成正相关;交通流差异与出行者认知阈值成负相关;纯电动汽车的使用会降低交通系统的效率.

关键词: 纯电动汽车;约束路径;强化学习; 有限理性; 交通流动态

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