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# Analysis of the traffic running cost under random route choice behavior in a network with two routes

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## HIGHLIGHTS

- The car-following model is utilized to explore the driving behavior in a network.
- Each driver's three running costs are studied in a network.
- Three total running costs are studied in a network.

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## ABSTRACT

In this paper, a car-following model is used to study each driver's three running costs in a network with two routes under the random route choice behavior. The numerical results indicate that each driver's three running costs and the corresponding total cost are relevant to the gap of the time the driver enters the network. The results can help us to further explore each driver's trip cost in a more complex network under other route choice behavior.



## 1. Introduction

To date, researchers used traffic flow theory to study the commuter's traffic cost under different traffic situations [1–4]. For example, Newell [1] used the LWR (Lighthill–Whitham–Richards) model [5,6] to explore the commuter's trip cost during the morning rush hour. Later, Arnott and his coauthors [2–4] extended the work based on the bottleneck model [7]. The studies [1–4] can describe some interesting results of the commuter's trip cost during the morning rush hour, but the methods [1–4] cannot be used to directly study the relationships between the commuter's micro driving behavior and his trip cost (especially considering the energy consumption and the emission toll) since the LWR model cannot be used to explore the commuter's micro driving behavior. To conquer this drawback, Tang et al. [8–12] used a car-following model to study the driver's running costs and corresponding trip costs on a road with open boundary and found that the driver's running costs and trip costs are both related to his time headway at the origin. However, Tang et al. [8–12] made two assumptions, i.e., the driver's departure time is an exogenous variable and each driver runs on a road with open boundary. In fact, each driver runs in a network with multi routes. So, the methods proposed in the studies [1–4,8–12] cannot be used to study the driver's running cost and corresponding trip cost in a network with multi routes. In addition, many traffic flow models were proposed to study various complex traffic phenomena [13–54], where the models can roughly be classified into the macro

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models [13–30] and the micro models [31–55]. However, the micro models (especially the car-following models) have not been used to study the running costs in a network, yet. In this paper, we use a car-following model to explore each driver's running cost and the total costs in a simple network with two routes under the random route choice behavior.

## 2. Model formulation

The car-following model is a kind of important micro models, where the generalized car-following model can be formulated as follows:

$$\frac{\mathrm{d}v_n}{\mathrm{d}t} = f\left(v_n, \Delta x_n, \Delta v_n, \ldots\right), \tag{1}$$

where $v_n$, $\Delta x_n$, $\Delta v_n$ are the $n$th vehicle's speed, headway and relative speed, respectively; $f$ is the stimulus function determined by the $n$th vehicle's speed, headway, relative speed and other related factors. However, Eq. (1) cannot reproduce the influences of real-time road condition on the driving behavior since this factor is not considered, so Tang et al. [56] proposed a car-following model accounting for real-time road condition, i.e.,

$$\begin{aligned}\frac{\mathrm{d}v_n(t)}{\mathrm{d}t} &= \kappa\left(\left(1+\varepsilon_r\left(R\left(x_n+\varDelta, t\right)-R\left(x_n, t\right)\right)\right)V\left(\Delta x_n(t)\right)-v_n(t)\right)\\ &\quad+\lambda\Delta v_n(t)+\mu_r\left(R\left(x_n+\varDelta, t\right)-R\left(x_n, t\right)\right)\cdot a_r,\end{aligned} \tag{2}$$

where $R$ is one real-time variable reflecting real-time road condition; $a_r$ is the adjustment term resulted by the real-time road condition; $\kappa$, $\varepsilon_r$, $\lambda$, $\mu_r$ are four reaction coefficients; $V(\cdot)$ is the optimal velocity. Tang et al. [56] defined $R$ as a random digit in the interval $[-1, 1]$, where $R > 0$ means good road, $R = 1$ means the best road; $R = 0$ means neutral road; $R < 0$ means bad road; $R = -1$ means the worst road. The optimal speed is here defined as follows [56]:

$$V\left(\Delta\bar{x}\right) = 19.037\mathrm{e}^{-18.94\frac{1}{\Delta\bar{x}+l}}, \tag{3}$$

where $l = 5$ m is the vehicle's average length.

The parameters $\varepsilon_r$, $\mu_r$, $a_r$ are defined as follows [56]:

$$\varepsilon_r = \mu_r = \begin{cases}0, & \text{if } \Delta x_n < 25.25 \text{ or } \Delta x_n > 100\\ 0.2, & \text{otherwise,}\end{cases} \tag{4}$$

$$a_r = \begin{cases}0, & \text{if } \Delta x_n < 25.25 \text{ or } \Delta x_n > 100\\ 0.2, & \text{otherwise.}\end{cases} \tag{5}$$

The parameters $\kappa$, $\lambda$ are defined as follows [31]:

$$\kappa = 0.41, \lambda = \begin{cases}0.5, & \text{if } \Delta x_n \le 100\\ 0, & \text{otherwise.}\end{cases} \tag{6}$$

Since Eq. (2) has considered the real-time road condition, we in this paper use it to describe each vehicle's motion on each route in a network with two routes. Note: we can obtain the similar results if we apply other car-following models to describe each vehicle's motion in the network.

Next, we should define each driver's running costs. Before defining the running costs, we should assume that each driver and each vehicle are both homogeneous. Thus, we can define each driver's three running costs, i.e.,

$$T_n^{\mathrm{I}} = \alpha t_n, \tag{7a}$$

$$T_n^{\mathrm{II}} = \alpha t_n + \beta\,(\mathrm{FC})_n, \tag{7b}$$

$$T_n^{\mathrm{III}} = \alpha t_n + \beta\,(\mathrm{FC})_n + \gamma_1\,(\mathrm{HC})_n + \gamma_2\,(\mathrm{CO})_n + \gamma_3\,(\mathrm{NO}_X)_n, \tag{7c}$$

where $T_n^{\mathrm{I}}$, $T_n^{\mathrm{II}}$, $T_n^{\mathrm{III}}$ are the $n$th driver's first, second and third running costs, respectively; $\alpha$ is the value of time; $t_n$ is the $n$th driver's running time; $\beta$ is the fuel price; $(\mathrm{FC})_n$ is the $n$th driver's fuel consumption; $\gamma_1$, $\gamma_2$, $\gamma_3$ are the tolls of HC, CO and $\mathrm{NO}_X$, respectively; $(\mathrm{HC})_n$, $(\mathrm{CO})_n$, $(\mathrm{NO}_X)_n$ are the $n$th driver's total HC, CO and $\mathrm{NO}_X$, respectively.

Thus, we can define three total costs as follows:

$$T_{\mathrm{total}}^{\mathrm{I}} = \sum_{n=1}^{N_0} T_n^{\mathrm{I}}, \tag{8a}$$

$$T_{\mathrm{total}}^{\mathrm{II}} = \sum_{n=1}^{N_0} T_n^{\mathrm{II}}, \tag{8b}$$

$$T_{\mathrm{total}}^{\mathrm{III}} = \sum_{n=1}^{N_0} T_n^{\mathrm{III}}, \tag{8c}$$

where $T_{\mathrm{total}}^{\mathrm{I}}$, $T_{\mathrm{total}}^{\mathrm{II}}$, $T_{\mathrm{total}}^{\mathrm{III}}$ are three corresponding total costs, respectively; $N_0$ is the corresponding number of drivers.