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Balancing congestion and emissions in urban networks via path-based incentives

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SHORT SUMMARY

This study investigates the potential of path-based incentives to mitigate congestion and reduce emissions in urban transport networks using a multi-objective optimisation problem with a budget limit. A column generation-based solution technique is developed that finds a new path between each origin-destination pair at each iteration, and stops when the objective value does not change more than a threshold at two consecutive iterations. Three different scenarios are defined based on the objective function: minimising total travel time (TTT), total emissions (TE), and integrated minimisation of both. Numerical results in the Sioux Falls network show that TTT and TE are conflicting objectives under our modeling assumptions: improving one worsens the other. Nonetheless, the integrated scenario demonstrates the capacity to harmonize both objectives, thereby achieving a reduction in both TTT and TE.

Keywords: Incentive scheme; Traffic assignment; System optimum; Traffic management.

1 INTRODUCTION

Providing drivers with sensible route advice is considered a successful traffic management tool, with the potential to reduce congestion (Kaysi, 1993; Fu, 2001; Cheng et al., 2020; Menelaou et al., 2021) and, thereby, improve network efficiency and sustainability (Sunio & Schmöcker, 2017; Andersson et al., 2018), although it may increase individual travel cost (distance and/or time) for some users (van Essen et al., 2016). This implies that some drivers may need to follow routes longer than desirable for the benefit of the community, translating to system optimum (SO) condition, which is in contrast to user equilibrium (UE) aiming at achieving the highest individual benefits (Mahmassani & Peeta, 1993). Thus, a stimulus, e.g., road pricing or incentive, is needed to encourage such changes in drivers' behaviour. Recently, incentivising schemes for voluntary participation (Ettema et al., 2010; Leblanc & Walker, 2013; Sun et al., 2020; Cohen-Blankshtain et al., 2022) have gained more popularity due to public dissatisfaction (May et al., 2010) and inequitable welfare distribution across the population (Levinson, 2010; Vosough et al., 2022) resulted from road pricing.

Bie & van Arem (2009) investigated the impact of applying path incentives to designated safe routes on traffic network performance. Their numerical results indicated that, depending on the incentive program setup, the incentive scheme can be beneficial or not. Mei et al. (2017) designed a personalized incentive framework generated by processing travel information through a decision tree and evolutionary game theory to adjust the mode and route choices of travellers while taking into account a balance between multiple goals. Xiong et al. (2020) employed personalized monetary incentives to adjust the departure time and route choice of travellers to minimize energy consumption. They observed that by offering an incentive 27% of travellers would change their routes while 20% would change their departure time, and the system can achieve 8.7% energy saving. Finally, Ghafelebashi et al. (2023) proposed a path-based personalised incentive chosen

from a predetermined set to minimise total travel time (TTT) under various budget limits and user participation levels of the incentive scheme. They showed that the value of saved time was usually larger than the cost of offering incentives, however, for large budget limits the value of saved time might be smaller than the amount spent on incentives.

Recently, [Luan et al. \(2023\)](#) conducted a comparison between link- and path-based incentives to analyse their potential to reduce TTT, by formulating single-level optimisation problems to compare the two types of incentives under budget limits and various participation levels of drivers. Their numerical examples in two transportation networks showed that in most cases path-based incentives outperformed link-based incentives.

Traditionally, an SO condition prioritises the minimisation of TTT; however, with the recent growth in population and urbanisation, air pollution has emerged as a significant challenge in cities that needs to be addressed. However, TTT and total emissions (TE) are conflicting objectives; minimising one leads to an increase in the other. Hence, jointly optimising them requires special attention to provide a balance between TTT and TE. In this work, we bridge this fundamental gap as follows:

1. We introduce an optimisation problem aimed at maximising the efficiency of the network, i.e., jointly minimising TTT and TE, under path-based incentive schemes within the constraints of a limited budget; and
2. we propose an innovative solution algorithm capable of solving path-based incentive optimisation problems efficiently in medium-sized transportation networks.

2 METHODOLOGY

In this section, we formulate the path-based problem as a single-level optimisation problem to determine the optimal incentive schemes under budget limitations.

2.1 Path-based incentive optimisation problems

We represent a transportation network by a graph (V, A) , where V is the set of nodes and $A \subset V \times V$ is the set of links. Let $W \subset V \times V$ be the set of OD pairs, and let the travel demand, q_w , be described by the fixed number of vehicles travelling between $w \in W$.¹ Table 1 defines all the parameters and variables used in the proposed formulation.

The single-level optimisation problem with a budget limit, B , is formulated as follows:

$$\min Z(\mathbf{f}, \mathbf{y}) \tag{1}$$

s.t.

$$\sum_{p \in P_w} f_w^p = q_w \quad \forall w \in W \tag{2}$$

$$\sum_{a \in A} \delta_a^p t_a - y^p - u_w \geq 0 \quad \forall p \in P_w, w \in W \tag{3}$$

$$(\sum_{a \in A} \delta_a^p t_a - y^p - u_w) f_w^p = 0 \quad \forall p \in P_w, w \in W \tag{4}$$

$$\sum_{w \in W} \sum_{p \in P_w} f_w^p y^p \leq B \tag{5}$$

$$x_a = \sum_{w \in W} \sum_{p \in P_w} \delta_a^p f_w^p \quad \forall a \in A \tag{6}$$

$$t_a = t_a(x_a) \quad \forall a \in A \tag{7}$$

$$\mathbf{f}, \mathbf{y}, \mathbf{u} \geq 0 \tag{8}$$

The objective function, Z , minimises transportation externalities, e.g., TTT and/or TE wrt. path flows and incentives, $\mathbf{f}$ and $\mathbf{y}$. Constraint (2) guarantees that vehicles reach their destinations, Constraints (3) and (4) are the complementarity constraints ensuring Wardrop's first principle with generalised travel cost that is defined as the path travel time minus path incentive ($\sum_{a \in A} \delta_a^p t_a - y^p$), Constraint (5) imposes the budget limitation, Constraint (6) maps path flows to link flows, Constraint (7) is the link cost function, defined as a general nonlinear function of the link flow x_a and Constraint (8) ensures non-negativity.

¹We acknowledge the potential risk of induced car demand associated with incentive schemes. In our proposed method, we do not offer high incentives that could generate revenue for drivers, i.e., negative generalised travel cost. This restraint is guaranteed by Constraint (3). By refraining from assigning high incentives, we can assume that the attraction of travellers from other modes to car trips is prevented, leading to inelastic demand, q_w .

Table 1: Notation for variables and parameters

Symbol	Definition
A	Set of links
V	Set of nodes
W	Set of all OD pairs
q_w	Travel demand between OD pair $w \in W$
P_w	Set of all paths between OD pair $w \in W$
t_a	Travel time on link $a \in A$
x_a	Vehicle flows on link $a \in A$
f_w^p	Vehicle flows on path $p \in P_w$ between pair $w \in W$
y^p	Incentive on path $p \in P_w$ between pair $w \in W$
B	Total budget available for the path-based incentive
u_w	Minimum travel time between OD pair $w \in W$
δ_a^p	Link-path incident matrix
α	Weight of travel time in the objective function

2.2 Solution algorithm

In simple networks, where the number of paths is limited, the incentivised UE problem with a budget limit can be solved directly as a one-time optimization by enumerating all paths. In the case of a large-scale transportation network, the direct approach is not useful since it is computationally expensive to enumerate all the paths of the network (Niroumand et al., 2023). Therefore, a column generation approach is developed to generate new paths as required while the algorithm proceeds.

The following column generation method considers each path as a column, adds new columns at each iteration, and stops when the minimum iteration number, N , is reached and the relative difference of the objective value in two consecutive iterations falls below a predefined small value ϵ . The steps of the proposed column generation algorithm are as follows:

1. Initialisation:

- (a) Define values for N and ϵ .
- (b) For each OD pair $w \in W$, set $P_w = \emptyset$.
- (c) Set $n = 1$, $\mathbf{y} = 0$, $\mathbf{f} = 0$, $\mathbf{x}^0 = \mathbf{x}(\mathbf{f})$, and $\mathbf{t}^0 = \mathbf{t}(\mathbf{x}^0)$.

2. Shortest path: for each OD pair $w \in W$,

- (a) Find the shortest path p such that $p \notin P_w$, and
- (b) set $\bar{P}_w = \bar{P}_w \cup p$.

3. User equilibrium: solve the optimisation problem, and find traffic flows $\mathbf{f}$, and corresponding incentive values $\mathbf{y}$.

4. Updating: set $\mathbf{x}^n = \mathbf{x}(\mathbf{f})$ and $\mathbf{t}^n = \mathbf{t}(\mathbf{x}^n)$.

5. Stopping criteria:

- (a) Calculate $\bar{\epsilon} = \frac{|\sum_{a \in A} (x_a^n t_a^n) - \sum_{a \in A} (x_a^{n-1} t_a^{n-1})|}{\sum_{a \in A} (x_a^n t_a^n)}$.
- (b) If $\bar{\epsilon} \leq \epsilon$ and $n \geq N$ stop, otherwise set $n = n + 1$ and go to step 2.

Note that we generate a new path that does not belong to the current active path set at each iteration of the column generation process to prevent getting trapped around a local optimum. However, such a path cannot be found by solving a standard shortest path problem. We, therefore, solve the mixed integer linear problem shown in equations (9)–(13) to find the shortest path between each OD pair while imposing a high penalty for choosing a path between OD pair $w \in W$ that already exists in the current active path set.

$$\lambda_w = \min_{\beta} \sum_{a \in A} (\beta_a t_a) + \sum_{p \in \bar{P}_w} (M \rho^p) \quad (9)$$

s.t.

$$\sum_{a \in A} |\delta_a^p - \beta_a| \geq 1 - \rho^p \quad \forall p \in \bar{P}_w \quad (10)$$

$$\sum_{a \in A: \text{start}(a)=v} \beta_a - \sum_{a \in A: \text{end}(a)=v} \beta_a = \begin{cases} +1 & \text{if } v \text{ is the origin node} \\ -1 & \text{if } v \text{ is the destination node} \\ 0 & \text{otherwise} \end{cases} \quad \forall v \in V \quad (11)$$

$$\beta_a \in \{0, 1\} \quad \forall a \in A \quad (12)$$

$$\rho^p \in \{0, 1\} \quad \forall p \in \bar{P}_w \quad (13)$$

Where β_a is a binary variable that equals 1 if link a is on the shortest path and 0 otherwise. Similarly, ρ^p is a binary variable that takes the value of 1 if path p is selected as the shortest path that already belongs to the current active path set $\bar{P}_w$ and 0 otherwise. The objective function (9) selects a set of links with the least travel time while penalizing choosing one of the current active paths with a big coefficient, M . Constraint (10) ensures that the variable ρ^p takes the value of 1 if and only if all constituting links of path $p \in \bar{P}_w$ exist in the shortest path found by the optimization model. Constraint (11) makes sure that the solution of the model is a path. Note that $\text{start}(a)$ and $\text{end}(a)$ indicate the starting and end nodes of link a .

Constraint (10) is nonlinear due to the presence of absolute value functions. A linearised version can be used to reduce its complexity. We linearise absolute value functions by introducing non-negative variables $(\eta_a^p)^+$ and $(\eta_a^p)^-$ and binary variable ϕ_a^p . We first set the argument of each absolute value function equal to the subtraction of the two non-negative variables as shown in the following equation.

$$\delta_a^p - \beta_a = (\eta_a^p)^+ - (\eta_a^p)^- \quad \forall p \in \bar{P}_w, a \in A \quad (14)$$

Then, the following constraints ensure that one of the non-negative variables, $(\eta_a^p)^+$ and $(\eta_a^p)^-$, take the value of zero using the big-M method.

$$(\eta_a^p)^+ \leq M \phi_a^p \quad \forall p \in \bar{P}_w, a \in A \quad (15)$$

$$(\eta_a^p)^- \leq M(1 - \phi_a^p) \quad \forall p \in \bar{P}_w, a \in A \quad (16)$$

Therefore, the output of the absolute value function becomes equal to the summation of the two non-negative variables.

Constraint (10) is finally linearised by replacing the absolute value functions with the summation of their associated non-negative values as follows.

$$\sum_{a \in A} ((\eta_a^p)^+ + (\eta_a^p)^-) \geq 1 - \rho^p \quad \forall p \in \bar{P}_w \quad (17)$$

Therefore, the linearised shortest path problem optimises the cost function (9), subject to constraints (14)–(17) and (11)–(13). Note that the column generation-based approach in principle can lead to the optimal solution if it iterates long enough to enumerate all the paths of the network. However, it can be stopped when the improvement in two consecutive iterations falls below a certain threshold resulting in a balance between computation time and solution quality.

3 NUMERICAL EXPERIMENT

The well-known Sioux Falls (SF) network, shown in Figure 1, is employed to show the ability of the proposed approach to reduce TTT and TE using incentive schemes. As link cost function (7), we employ the volume-delay BPR function (HCM, 2000)

$$t_a(x_a) = t_a^0 \left(1 + 0.15 \left(\frac{x_a}{C_a} \right)^4 \right), \quad (18)$$

where t_a^0 is the free flow travel time in link a and c_a its capacity in vehicles per time unit. The details of the links and OD matrix are sourced from He et al. (2014). This network consists of 24 nodes, 76 links, and 552 OD pairs. We employ the proposed column generation method to solve

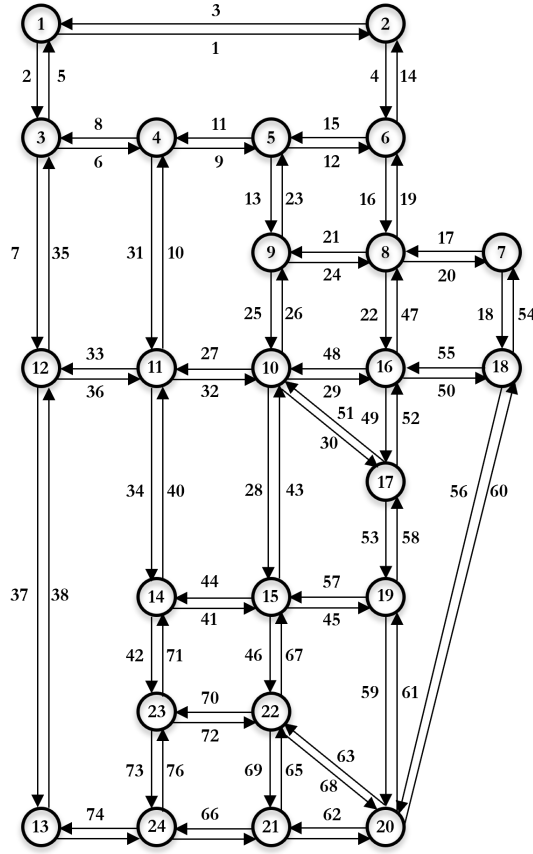


Figure 1: Sioux Falls network

the proposed optimisation problem for this network. It is worth noting that incentives and budgets are considered in the same unit as travel time, which is in minutes.

We assume emissions are proxied by CO2, and the CO2 rate per vehicle kilometre travelled in link a is computed according to [Dimitriou et al. \(2009\)](#)

$$E_a = 72.73 + 33.98 \times 10^2 / s_a + 23.26 \times 10^{-3} s_a^2, \quad (19)$$

where s_a is the average speed of link a in km/hr and E_a is in g/veh-km. This function used in macroscopic problems, has a U-shaped dependence on vehicle speed with respective minima at 42 km/hr.

3.1 Total travel time and total emission minimisation

We initially define two scenarios for testing the optimisation problem, considering two objective functions: TTT minimisation and TE minimisation. Under the TTT minimisation scenario, we minimise the total travel time, represented as $Z = \sum_{a \in A} (x_a t_a)$, and under TE minimisation scenario, we minimise the total emissions of the network, represented as $Z = \sum_{a \in A} (x_a E_a l_a)$, where l_a is the length of link a (in km). TTT and TE under the two scenarios with various budget limits are shown in Figure 2. It can be seen that targeting only TTT leads to an increase in total CO2 emitted in the network. On the contrary, targeting only TE brings about increased TTT. This is due to the fact that the minimum CO2 occurs when the average speed on a link is 42 km/h while for minimising TTT, the higher the average speed the better. Figure 3 illustrates how an incentive scheme changes the average speed to direct the traffic flow from UE toward SO by redistributing the traffic subject to the budget limit. According to this figure, targeting TTT minimisation smooths vehicle statistics and increases the average speed in most of the links but not necessarily in the direction of reducing emissions. For instance, the average speeds on links between nodes 11 and 14, and 21 and 24 have increased while the emissions fall in a higher range. However, in the case of targeting CO2 minimisation, the changes in the average speeds occurred

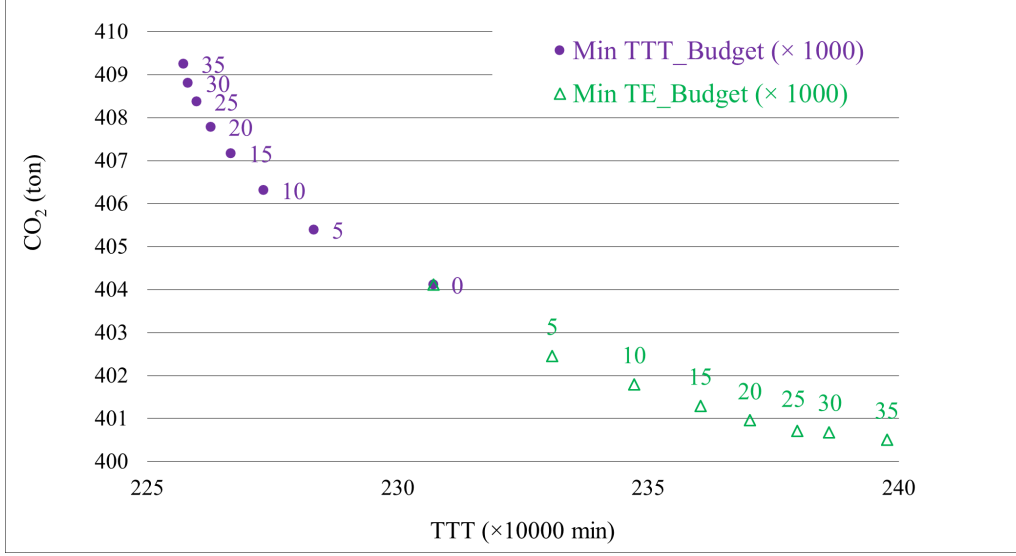


Figure 2: TTT and TE under total travel time minimisation and total emissions minimisation scenarios, with various budget limits

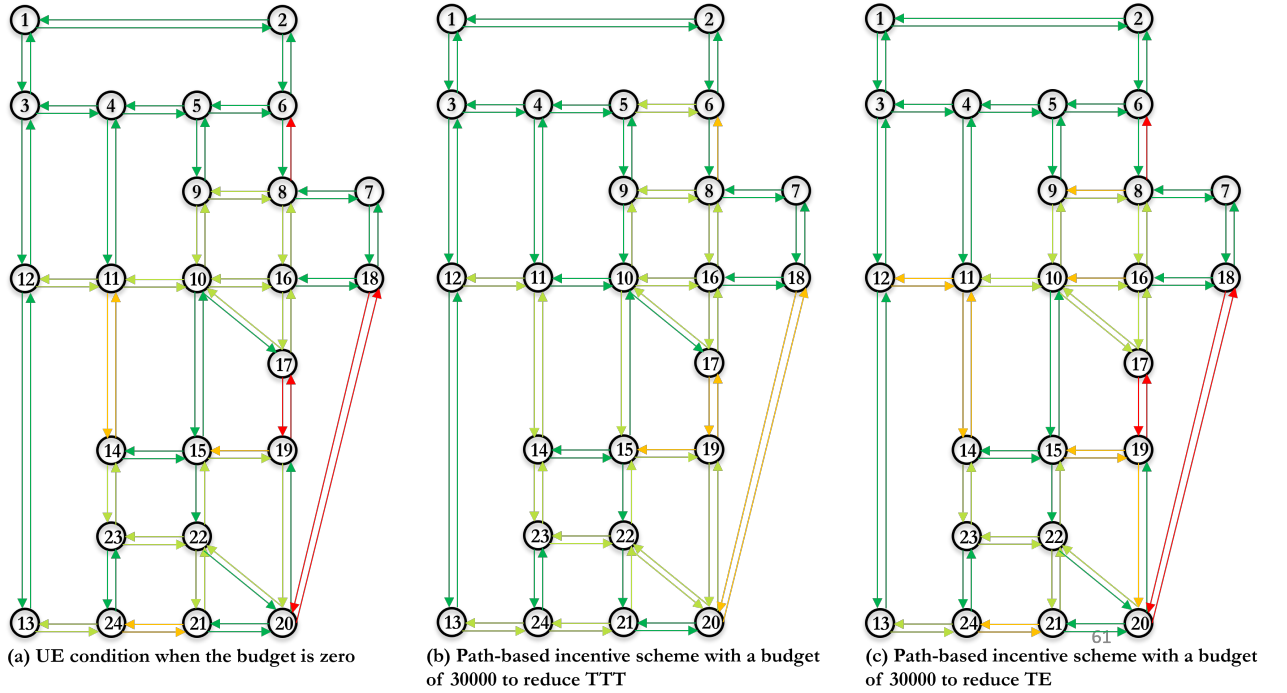


Figure 3: The changes in link speeds before and after implementing an incentive scheme, where dark green arrows represent $55 < s_a$, light green is $45 < s_a \leq 55$, orange illustrates $35 < s_a \leq 45$, and red arrows are $s_a \leq 35$ km/hr.

only to reduce the CO₂ emissions, such as decreased average speed of links between nodes 11 and 12 compared to the base case scenario.

3.2 Integrated total travel time and total emission minimisation

As it is shown in Figure 2, TTT and TE are conflicting objectives; minimising one leads to an increase in the other. Minimising the sum of TTT and TE without normalization and proper weighting will result in the improvement of the dominant objective term while exacerbating the other. Therefore, we normalize the two terms of the objective in such a manner that they attain a value of zero under the UE flow pattern and a value of one under the SO flow pattern when

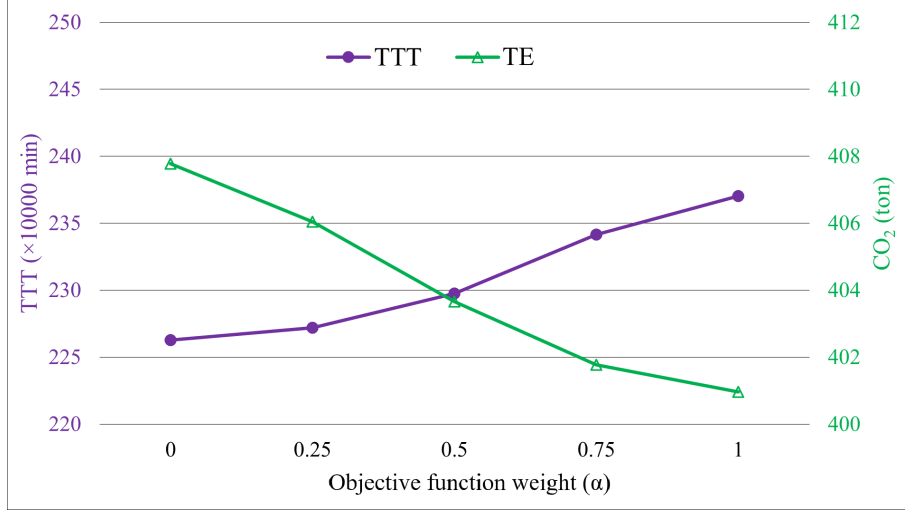


Figure 4: Total travel time and total emissions with different objective weight values and a budget limit of 20000

they are the sole objective of the minimisation. We define ξ^{UE} , ξ^{SO} , T^{UE} , T^{SO} , and α as the TE under UE and SO flow patterns, TTT under UE and SO flow patterns, and the weight of the objective function, respectively, to formulate the objective function of the integrated minimisation as follows:

$$Z = \min_{\mathbf{f}, \mathbf{y}} \left(\alpha \cdot \frac{\xi^{UE} - \sum_{a \in A} (E_a x_a l_a)}{\xi^{UE} - \xi^{SO}} + (1 - \alpha) \cdot \frac{T^{UE} - \sum_{a \in A} (x_a t_a)}{T^{UE} - T^{SO}} \right) \quad (20)$$

We initially conduct a sensitivity analysis on the objective function weight, α , to find an appropriate value that achieves a balance between TTT and TE. The optimisation problem (9)–(13) with the objective cost (20) is solved under a budget limit of 20000, using objective weight values ranging from zero to one at 0.25 increments. TTT and TE for each optimisation are summarized in Figure 4. As the objective weight value increases, the optimal solution emphasizes emission minimisation, resulting in lower emissions but longer TTT and vice versa. An objective weight value of 0.5 creates a balance between TTT and TE of the network. Therefore, we continue our analysis using 0.5 as the objective weight value.

Figure 5 depicts TTT and TE under different budget limits. Both TTT and TE decrease as the budget limit increases from 0 to 10000. However, increasing the budget limit from 10000 to 35000 does not consistently improve both efficiency metrics; one metric needs to increase to see a reduction in the other. This discrepancy arises from the conflicting nature of the two terms in the objective function, whereby improving both beyond a certain threshold becomes unfeasible. Note that the overall objective value of the optimization problem consistently decreases.

4 CONCLUSIONS

This study employs a path incentives scheme to shift the user equilibrium flow pattern towards the system optimum, aiming to minimise TTT, TE, and the weighted sum of TTT and TE. Wardrop's first principle is applied to generalised travel cost, defined as travel time minus path incentives. The problem is formulated as a nonlinear optimisation problem with complementarity constraints. Due to the computational expense of generating all paths for a real-sized network, an iterative column-generation-based solution technique is proposed. This technique generates a new path between each origin-destination pair at each iteration. Results from the case study on the Sioux Falls network indicate a conflict between TTT and TE. Therefore, joint optimisation of the two objectives, with proper normalization and weighting, is required to achieve a balance between TTT and TE reduction. Moreover, both TTT and TE show a decreasing trend up to a budget limit of 10000. However, the optimization model has to compromise on one of the objective terms to improve the other and achieve an overall better objective value beyond a budget limit of

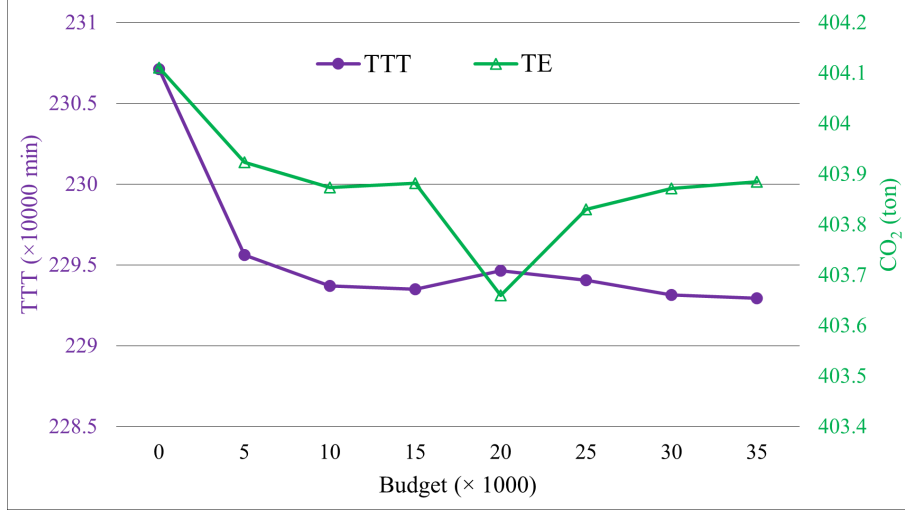


Figure 5: Total travel time and emissions with different budget limits

10000. Additionally, the reduction in both objectives under the joint optimisation scenario may not necessarily decrease with respect to increased budget limit.

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