PROMOTING ZERO-EMISSIONS VEHICLES USING ROBUST MULTI-PERIOD TRADABLE CREDIT SCHEME

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Abstract

This study designs a robust multi-period tradable credit scheme (TCS) to incentivize travelers to shift from internal combustion engine vehicles (ICEVs) to zero-emissions vehicles (ZEVs) over a long-term planning horizon to reduce vehicular emissions. The need for robust design arises because of uncertainty in forecasting travel demand over a planning horizon in the order of several years. The robust multi-period TCS design is formulated as a bi-level model. In the upper level, the central authority (CA) determines the TCS parameters (credit allocation and charging schemes) by vehicle type to minimize the worst-case vehicular emissions rate, i.e. the maximum vehicular emissions rate under the possible travel demand scenarios. The upper-level model is a mixed-integer nonlinear program. In the lower level, travelers minimize their generalized travel costs under the TCS parameters obtained in the upper level. These parameters are used to determine the vehicle type choice, between ICEVs and ZEVs, using a binomial logit function, and influence route selection based on the difference in credits charged on links for these two vehicle types. The

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lower-level model is a mathematical program with equilibrium constraints. The bi-level model is solved using a cutting plane method. Numerical experiments illustrate that the incentive to shift to ZEVs is fostered by allocating more credits and charging fewer credits to ZEV travelers compared to ICEV travelers. Further, the proposed TCS design reduces volatility in the realized vehicular emissions rates under different travel demand scenarios compared to a TCS design that does not consider demand uncertainty.

*Keywords*: Multi-period tradable credit scheme; zero-emissions vehicles; travel demand uncertainty; robust design.

1. **Introduction**

1.1. **Background**

Traffic congestion and consequent greenhouse gas (GHG) emissions are major quality-of-life issues in metropolitan areas. The European Union (EU) has targeted at least 80% reduction in GHG emissions by 2050 (UNFCCC, 2015), and the United States has sought to reduce, by 2025, its GHG emissions by 26-28% below the 2005 level (The White House, 2015). Also, in the U.S., the transportation sector accounted for 26.4% of GHG emissions in 2016, with cars and trucks accounting for 83.1% of that amount (EPA, 2016). Hence, managing traffic congestion and developing strategies to reduce usage of the high-emitting internal combustion engine vehicles (ICEVs) are critical for eventually reducing GHG emissions.

Transportation emissions reduction strategies have been classified into two groups (Litman, 2013). The first group focuses on mobility management strategies such as congestion pricing and tradable credit scheme (TCS). For example, Liu et al. (2009) propose the notion of revenue-neutral
congestion pricing to reduce vehicular emissions by motivating travelers to use transit instead of automobiles. Under this scheme, the revenue generated from congestion pricing is redistributed to travelers. However, since the central authority (CA) is the sole toll collector, the claim of revenue-neutrality is difficult to prove. Hence, Yang and Wang (2011) argue that this scheme may not receive public acceptance in practice and therefore, propose the concept of TCS which consists of credit allocation and charging schemes. In this concept, a CA determines the number of credits to allocate to travelers (credit allocation scheme) and the number of credits to charge for link usage (credit charging scheme). Travelers can trade credits in the market according to their credit endowments and travel needs. TCS is a promising alternative to congestion pricing (Miralinaghi and Peeta, 2016; Nie and Yin, 2013). In contrast to congestion pricing, a TCS does not entail transfer of wealth between travelers and CA, and can reduce vehicular emissions by managing travel demand and route choice of travelers.

The second group focuses on promoting alternative fuel vehicles, such as natural gas and hybrid vehicles that have fewer emissions compared to ICEVs. Zero-emissions vehicles (ZEVs) are alternative fuel vehicles that do not emit pollutants harmful to humans and the environment. Battery electric and hydrogen vehicles are well-known examples of ZEVs. Despite the potential benefits of ZEVs, their adoption has several barriers such as high retail prices, lack of refueling infrastructure (Shahraki et al., 2015; Sun et al., 2016; Wu and Sioshansi, 2017), and public acceptance (Krause et al., 2013). Strategies such as fuel tax increase and subsidy programs have been proposed to increase the adoption of ZEVs in practice. However, there is potential political resistance to fuel tax increases (de Palma and Lindsey, 2011).
1.2. Literature review

Quantity-based instruments have recently been proposed to manage traffic congestion. The European Union Emissions Trading System is a well-known practical example of implementing quantity-based strategies to reduce GHG emissions. In the context of traffic congestion externalities, Verhoef et al. (1997) propose the notion of “tradable road-pricing smart card” to manage road congestion and vehicular emissions. Nagurney et al. (2000; 1998) propose a system of origin-destination (O-D), path-based, and link-based pollution permits to achieve certain environmental goals. As a type of quantity-based instrument, studies have explored TCS to: (i) relax market assumptions (Nie, 2012; Shirmohammadi et al., 2013), (ii) analyze the effects of traveler characteristics under TCS (Bao et al., 2014; Wang et al., 2012), and (iii) understand the effects of TCS implementation on traffic dynamics (Miralinaghi et al., 2017; Ye and Yang, 2013). Grant-Muller and Xu (2014) provide a comprehensive review of literature on application of TCS in the context of mobility, parking, and bottleneck managements. Their review suggest that TCS can have advantage over congestion pricing especially in terms of efficiency and distribution of costs and benefits. Similarly, Dogterom et al. (2016) demonstrate that TCS has the potential to lead to further car usage reduction compared to congestion pricing.

Miralinaghi and Peeta (2016) label the aforementioned TCS models as “single-period TCS,” as they assume travel demand rates, credit supply and credit price to be constant. The only exception is the day-to-day model of Ye and Yang (2013) in which the credit price fluctuates for a few days before converging to equilibrium. The single-period TCS is not an appropriate tool for the CA due to the long-term nature of the GHG emissions reduction goal, which involves a planning horizon of several years. To address long-term system-level goals, Miralinaghi and Peeta
propose a multi-period TCS framework that enables the CA to factor long-term fluctuations in travel demand/supply. In this framework, the planning horizon is divided into multiple periods of equal length. These periods are in order of multiple years. The CA determines the credit allocation and charging schemes, referred to as TCS parameters, in each period to achieve system-level goals. Travelers may transfer unused credits to future periods based on several factors such as projected credit prices in future periods, current TCS parameters, current travel demand and traffic network supply. The multi-period TCS has two benefits in practice. First, it allows the CA to design the TCS so as to make steady progress toward system-level goals through the planning horizon. This also enables travelers to gradually adapt to the TCS implementation in practice. For example, the EU seeks to gradually reduce the emissions cap from 97% average of the 2005 values in 2012 to 95% in 2020, and 80% in 2050 (Leggett et al., 2012). Second, it can reduce credit price fluctuation through the planning horizon which mitigates travelers’ monetary losses when they trade or transfer credits (Miralinaghi and Peeta, 2016).

1.3. Research gaps and challenges

To reduce GHG emissions, several subsidy programs have been implemented to promote ZEVs in the U.S.. However, they can entail significant monetary burden for the government. For example, California Environmental Protection Agency (CalEPA) provides a rebate up to $5000 for the purchase of ZEVs under the clean vehicle rebate project\(^1\). Up to April 2017, CalEPA has invested about $288 million to fund rebates for zero-emissions vehicles (Center for Sustainable Energy, 2017). Despite this enormous investment, the adoption rate of ZEVs is still only 4.6% in California

\(^1\) https://cleanvehiclerebate.org/eng
(Global Automakers, 2017). Hence, there is a need to develop a new emission reduction strategy to promote ZEVs over a long-term planning horizon.

This paper proposes a hybrid approach combining the two groups of emissions reduction strategies using the concept of multi-period TCS to encourage the public to purchase and use ZEVs. In this context, the multi-period TCS is used to manage travel demand and travelers’ route choices, and promote ZEV adoption by rewarding travelers who generate fewer vehicular emissions. A key advantage of the proposed approach is its circumvention of monetary subsidies for the adoption of low-emissions vehicles. To design the multi-period TCS, CA needs to forecast travel demands over the long-term planning horizon. However, forecasting travel demand over a long-term planning horizon has inherent uncertainty. The reliability of travel demand forecasts diminishes as the length of the planning horizon increases. That is, near-term forecasts of travel demand have a higher degree of reliability compared to medium- or long-term forecasts over the planning horizon. This demand uncertainty can be attributed to changes in land use, economic and demographic characteristics. However, it has not been addressed in TCS-design studies.

1.4. Research approach and contributions

The study seeks to design a multi-period TCS so that enables a CA to minimize vehicular emissions over a long-term planning horizon while incentivizing the use of ZEVs. This study places travel demand as follows – ZEV and ICEV travelers. For simplicity, other types of alternative-fuel vehicles such as ethanol and natural gas fuel vehicles are not considered\(^1\). The TCS parameters of

\(^1\) The proposed multi-period TCS can be seamlessly extended to account for more than two vehicle classes based on vehicular emissions levels.
each period are designed to be vehicle type specific. They consist of: (i) vehicle type specific O-D based credit allocation scheme, i.e., credit allocation rate to travelers based on their vehicle type and O-D pair, and (ii) vehicle type specific link-based credit charging scheme, i.e. the number of credits charged to travelers for using a link based on the vehicle type. To implement the group specific credit charging scheme, different types of vehicle license plate can be issued to ZEVs and ICEVs and then, their travel can be tracked using the recent technological advancements of license plate readers. The idea of class differentiated tolling, e.g., by vehicle type, has been also investigated by other studies such as Holguin-Veras and Cetin (2009). The vehicle type choice of travelers is captured using a binomial logit function that incorporates the effects of favorable credit allocation and link credit charges for ZEVs.

To capture the uncertainty over the long-term planning horizon, we account for demand uncertainty and illustrate that it needs to be explicitly factored due to influence on the effectiveness of the multi-period TCS. It represents another novel aspect considered in this study. In mathematical programming, two methods have been proposed to address such uncertainty. The first method, referred to as stochastic programming (Dantzig, 1955), assumes different scenarios with corresponding probabilities of occurrence. However, it is difficult to estimate this probability distribution in practice. The second method proposes the concept of a robust approach (Bertsimas and Sim, 2003) which optimizes the system against the worst-case scenario while circumventing the need to estimate the probabilities of different scenarios. It has been applied previously to network design with demand uncertainty (Lou et al., 2009). In this study, we use the second method to develop a robust multi-period TCS design to reduce vehicular emissions.
Under the robust TCS design, travel demand for each O-D pair can be its average value or one of the values in its uncertainty set whose probabilities are unknown. The travel demand uncertainty set consists of the possible demand scenarios. The demand values are often forecast by the metropolitan planning organizations using econometric methods based on socioeconomic and land use characteristics. Bertsimas and Sim (2003) propose the notion of uncertainty budget. In our study, the budget is used to cap the total number of O-D pairs whose travel demands deviate from their average values in each period. It enables the CA to analyze the tradeoffs between computational burden and accuracy. For example, if the CA allows the demand of several O-D pairs to deviate from their average values, it can add significant computational burden due to the number of possible scenarios. Hence, the notion of uncertainty budget is used in robust design to enhance computational tractability. Another key advantage of the uncertainty budget in our study context is that it enables capturing the increasing degree of travel demand uncertainty through the planning horizon. This is because long-term forecasts have higher uncertainty compared to short-term forecasts; in other words, the uncertainty budget increases over the planning horizon. The robust TCS design model is solved using a cutting-plane method (Lawphongpanich and Hearn, 2004).

The following are the contributions of this study. First, to the best of our knowledge, this is the first study that leverages a TCS to circumvent the need for monetary subsidies to promote the low-emissions vehicles. Second, to the best of our knowledge, this is the first study with a hybrid approach that combines mobility management strategies and strategies that promote alternative fuels to reduce vehicular emissions. This hybrid approach synergistically aids the attaining of system-level environmental goals while promoting ZEV usage. Third, the proposed approach leads
to sustainable behavior of travelers in practice. Because, it incentivizes travelers to use ZEVs by designing TCS parameters that leads to higher utility for travelers and causes them to shift to ZEVs. Fourth, the study proposes a robust TCS design to account for demand uncertainty that is inherent to the long-term planning horizon for attaining the environmental goals. That is, the TCS parameters optimize the system against the worst-case vehicular emissions rate.

The numerical experiments in this study show that ZEV adoption is facilitated by allocating more credits to ZEV travelers and charging them fewer credits compared to ICEV travelers. Further, ZEV travelers can sell unused credits to ICEV travelers in a travel credit market and generate monetary gains. This further incentivizes travelers to adopt ZEVs, and contributes to the higher travel utilities for ZEV travelers compared to ICEV travelers. This ability to leverage the use of a multi-period TCS to promote ZEV usage provides a sustainable behavioral mechanism to achieve the CA’s system-level objective of reducing vehicular emissions. The numerical experiments further show that the robust design of multi-period TCS (RDMPTCS) leads to higher market penetration of ZEVs, which minimizes the worst-case vehicular emissions. It also reduces the volatility in realized vehicular emissions in practice under different travel demand scenarios compared to the system optimal multi-period TCS design that does not factor demand uncertainty. This increases the reliability of vehicular emissions reductions under travel demand uncertainty.

1.5. Organization

The remainder of this study is organized as follows. Section 2 introduces some preliminaries. Section 3 models the robust multi-period TCS design under travel demand uncertainty. Section 4 discusses the solution algorithm to solve for the robust multi-period TCS design. Section 5
discusses results and insights from numerical experiments. Section 6 provides some concluding
comments.

2. Preliminaries

Let $G(N, A)$ be a directed transportation network, where $N$ and $A$ denote the sets of nodes and
links of a transportation network, respectively. Let $w \in W$ denote the set of O-D pairs and $R_w$ the
set of all routes for O-D pair $w \in W$. The planning horizon is divided into $T$ independent periods
of equal length where the length of each period is in order of multiple years (e.g. five years). Let
$\Gamma$ denote the set of time periods. Travel demand and traffic network supply are constant within
each period but vary across periods. We consider a mixed traffic scenario consists of ZEV and
ICEV travelers where $M = \{1, 2\}$ denotes the set of vehicle types, in which vehicle type 1
corresponds to ZEV travelers and vehicle type 2 corresponds to ICEV travelers. The travel demand
rate of vehicle type $m$ of O-D pair $w$ in time period $t \in \Gamma$ is denoted by $q_{w,m}^{t}$. Let $d_{w}^{t}$ denote the
aggregate travel demand rate of O-D pair $w$ in time period $t$, that is $d_{w}^{t} = \sum_{m \in M} q_{w,m}^{t}$.

Let $v_{a,m}^{t}$ and $v_{a}^{t}$ denote the flow of vehicle type $m$ and aggregate flow on link $a$ in time period
$t$, respectively. Let $f_{r,w}^{t,m}$ denote the flow of vehicle type $m$ on route $r$ for O-D pair $w$ in time
period $t$. For a given aggregate demand vector $d = (d_{w}^{t}, t \in \Gamma, w \in W)^T$, $\Omega$ represents the feasible
vector of link flows $\nu^M = (v_{a,m}^{t}, a \in A, m \in M, t \in \Gamma)^T$, aggregate link flows $\nu = (v_{a}^{t}, a \in A)^T$,
vehicle-specific travel demand rates $q = (q_{w,m}^{t}, t \in \Gamma, w \in W, m \in M)^T$ and route flows $f^M =
(f_{r,w}^{t,m}, r \in R, t \in \Gamma, w \in W, m \in M)^T$ as follows:
\[
\Omega(d) = \left\{ \left( f^M, \nu^M, \nu \right) \mid \begin{align*}
\sum_{w \in W, r \in R_w} f_{r,w}^t m \delta_{a,r,w} &= \nu_a^t m , \\
\sum_{m \in M} &\nu_a^t m = \nu_a^t , \\
q_w^t m &= \sum_{r \in R_w} f_{r,w}^t m \forall m \in M, \forall t \in \Gamma, \forall w \in W, \forall r \in R_w \end{align*} \right\} \quad (1)
\]

where \( \delta_{a,r,w} = 1 \), if link \( a \) is on route \( r \) of O-D pair \( w \), and 0 otherwise. Let \( \mu_{w}^{t,m} \) denote the minimum generalized travel cost, including travel time and credit consumption costs, of vehicle type \( m \) for O-D pair \( w \) in time period \( t \). Let \( c_{a}^{t} \) denote the link travel time function for each link \( a \in A \) in period \( t \); it is assumed to be nonnegative, separable, differentiable, and monotonically increasing with aggregate flow of link \( a \), \( v_{a}^{t} \), of time period \( t \).

Under the multi-period TCS, the CA allocates credits at the average rate of \( \xi^{t} \) in each period \( t \). Let \( \xi = \{ \xi^{t}, \forall t \in \Gamma \} \) denote the vector of CA-issued credit rates. This study assumes that the CA implements the vehicle type specific credit allocation scheme \( n = \{ n_{w}^{t,m}, \forall w \in W, \forall m \in M, \forall t \in \Gamma \} \) under which travelers using each vehicle type \( m \) for O-D pair \( w \) in time period \( t \) receive credits at the rate of \( n_{w}^{t,m} \), i.e. \( \sum_{w \in W} \sum_{m \in M} n_{w}^{t,m} q_{w}^{t,m} = \xi^{t} \). Let \( u = \{ u_{a}^{t,m}, \forall a \in A, \forall m \in M, \forall t \in \Gamma \} \) denote the vehicle type specific link-based credit charging scheme under which travelers of vehicle type \( m \) are charged \( u_{a}^{t,m} \) credits for using link \( a \) at any time in period \( t \). Travelers sell the unused credits in each period \( t \) or transfer them to the future periods \( t' \) based on the current credit prices and credit price information of future periods \( t' \) in period \( t \), \( \gamma^{t,t'} \). It is assumed that the CA provides the information about future credit prices to travelers in each period. This information can be calculated by CA using the frameworks proposed by Miralinaghi (2018). Let \( \gamma = \{ \gamma^{t,t'}, \forall t < t', \forall t \in \Gamma \} \) denote the vector of information on future credit prices during the planning horizon. Let \( z^{t,t'} \) denote the credit transfer rates from period \( t \) to period \( t' \). The interest rates are assumed to be zero across the periods during the planning horizon, implying that they
cannot accrue interest by depositing credits in the bank. Further, travelers are assumed to be homogeneous in terms of how they value travel time. Their valuations are assumed to be constant within each period but change through the planning horizon. Let $\alpha^t$ denote the average value of time of travelers during period $t$. For clarity, the notations are summarized as follows:

Sets

- $N$: Sets of nodes
- $A$: Sets of links
- $W$: Set of O-D pairs
- $\Gamma$: Set of time periods
- $\mathcal{E}$: Uncertainty set
- $M$: Set of vehicle types
- $S$: Set of O-D travel demand scenarios

Vectors

- $d$: Vector of aggregate travel demands
- $\nu^M$: Vector of vehicle type specific link flows
- $\nu$: Vector of aggregate link flows
- $q$: Vector of vehicle-specific travel demands
- $f^M$: Vector of route flows
- $\xi$: Vector of credit allocation rates
- $n$: Credit allocation scheme
- $u$: Credit charging scheme
- $\gamma$: Vector of information on future credit prices
- $p$: Vector of equilibrium credit prices

Parameters

- $T$: Cardinality of set of time periods
- $\gamma^{t,t'}$: Credit price information of future periods $t'$ in period $t$
- $l^t_a$: Length (in kilometers) of link $a$ in period $t$
- $U^t$: Uncertainty budget
- $d_{w}^{t,s}$: Aggregate travel demand rate of O-D pair $w$ in time period $t$ under scenario $s$
- $\alpha^t$: Value of time of travelers in period $t$
- $\phi^t$: Maximum ratio of generalized travel cost after TCS implementation to the generalized travel cost without TCS for any O-D pair in period $t$
- $r$: Travel demand growth rate
- $\theta^s$: Parameter controlling the level of uncertainty for scenario $s$ of travel demand
Variables

\( q^t_{w,m} \)  
Travel demand rate of vehicle type \( m \) of O-D pair \( w \) in time period \( t \)

\( v^t_{a,m} \)  
Flow of vehicle type \( m \) on link \( a \) in time period \( t \)

\( \nu^t_a \)  
Aggregate flow on link \( a \) in time period \( t \)

\( f^t_{r,w} \)  
Flow of vehicle type \( m \) on route \( r \) of O-D pair \( w \) in time period \( t \)

\( d^t_w \)  
Aggregate travel demand rate of O-D pair \( w \) in time period \( t \)

\( \mu^t_{w,m} \)  
Minimum generalized travel cost of vehicle type \( m \) for O-D pair \( w \) in time period \( t \)

\( c^t_a \)  
Link travel time of link \( a \) in period \( t \)

\( \xi^t \)  
Total credit allocation rate in period \( t \)

\( e^t_a \)  
Emissions rate (in g/veh) of link \( a \) in period \( t \)

\( n^t_{w,m} \)  
Credit allocation rate to travelers using vehicle type \( m \) for O-D pair \( w \) in time period \( t \)

\( z^{t,t'} \)  
Credit transfer rate from period \( t \) to period \( t' \)

\( c^t_a \)  
Travel time (in minutes) of link \( a \) in period \( t \)

\( \eta^t_s \)  
Binary variable indicating whether scenario \( s \) is the worst-case demand scenario for O-D pair \( w \) in time period \( t \)

\( \mu^t_{w,E} \)  
Generalized travel cost without TCS of O-D pair \( w \) in period \( t \)

\( p^t \)  
Equilibrium credit price in period \( t \)

\( Y^T \)  
Credit discarding rate in the last period \( T \)

\( \lambda^t_{w,1} \)  
Extra cost for ZEV travelers compared to ICEV travelers of O-D pair \( w \) in period \( t \)

\( \varphi \)  
Maximum vehicular emissions rate under the possible demand scenarios

3. Robust Design of Multi-Period TCS (RDMPTCS)

This section presents the RDMPTCS. The RDMPTCS is a bi-level model and formulated as a bi-level model shown in Fig. 1. In the upper level, the CA determines the multi-period TCS parameters to minimize vehicular emissions rate for the travel demand scenario which causes the maximum emissions among possible demand scenarios, referred to as the worst-case vehicular emissions rate. Also, the generalized travel costs, consisting of travel time and credit consumption costs, are constrained from increasing beyond a predetermined bound in each period after the TCS implementation. The upper-level model is a mixed-integer nonlinear mathematical program. In the lower level, travelers minimize their
generalized travel costs through their choice of vehicle type and route under the multi-period TCS parameters obtained in the upper level. These parameters are used to determine the choice between ICEVs and ZEVs using a binomial logit function, and influence route selection based on the difference in credits charged on links for these two vehicle types. The lower-level model is a mathematical program with equilibrium constraints. First, section 3.1 presents the upper-level model. Then, section 3.2 discusses the lower-level model. Finally, section 3.3 formulates the robust multi-period TCS design.

3.1. Upper-level model

This section presents the upper-level model in which the CA aims to design TCS parameters to minimize the worst-case vehicular emissions rate. Let $e_a^t$ denote the GHG emissions rate of ICEV travelers using link $a$ in period $t$ which is assumed to be nonnegative and monotonically increasing with aggregate flow of link $a$, $v_a^t$, of time period $t$. The vehicular emissions rate of traffic network is equal to $\sum_{t \in T} \sum_{a \in A} v_a^t \cdot e_a^t(v_a^t)$ through the planning horizon.
In practice, travel demand rates of O-D pairs are forecasted by transportation planners. However, these forecasts are characterized by uncertainty due to alternative forecasts of socioeconomic and land use developments by metropolitan planning organizations during the planning horizon (Transportation Research Board of the National Academies, 2007). To account for the uncertainty in aggregate travel demand rates, it is assumed that the aggregate travel demand rate of each O-D pair in each period takes one of several values whose occurrence probabilities are unknown. We refer to this set of aggregate travel demand rates as an uncertainty set $\mathcal{E}$. Let $S$ denote the set of demand scenarios for each O-D pair, where each scenario is associated with a demand rate. Let $d_{w}^{t,s}$ denote the aggregate travel demand rate of O-D pair $w$ in time period $t$ under scenario $s$, where $d_{w}^{t,1}$ denotes the average aggregate travel demand rate of O-D pair $w$ in time period $t$. Based on the combinations across all O-D pairs during the planning horizon, the total number of demand scenarios in the network across all O-D pairs is finite and equal to $|S|^{|W|\times|T|}$ during the planning horizon. For example, 3 demand scenarios for each O-D pair in traffic network with 552 O-D pairs during 5 periods lead to $3^{552\times5}$ demand scenarios across all O-D pairs during the planning horizon.

Let $\eta_{w}^{t,s}$ denote the binary variable indicating whether scenario $s$ is the worst-case demand scenario for O-D pair $w$ in time period $t$. The demand uncertainty set, $\mathcal{E}$, can be defined as follows:

$$\mathcal{E} = \{d | \sum_{s \in S} d_{w}^{t,s} \eta_{w}^{t,s} = d_{w}^{t}, \sum_{s \in S} \eta_{w}^{t,s} = 1, \sum_{s \in S_{w}-\{1\}} \eta_{w}^{t,s} \leq U^{t}, \eta_{w}^{t,s} \in \{0,1\} \}$$

where $U^{t}$ is the uncertainty budget which allows at most $U^{t}$ travel demand rates of O-D pairs to deviate from their average values $d_{w}^{t,1}$ in period $t$. The uncertainty budget is used to reduce computational burden as it reduces the possible demand scenarios in the network to
\[
\left(\binom{w}{u_0}\right)^{1 \sim |S|} \cdot |S|^{\sum|U^t|} \text{ during the planning horizon. For the previous example, if the uncertainty budgets are equal to 45, the total number of demand scenarios across all O-D pairs in the network reduces to } \left(\binom{552}{45}\right)^5 \cdot |3|^{45 \times 5} \text{ during the planning horizon. As the uncertainty budget can significantly reduce the number of possible demand scenarios across all O-D pairs, it can preclude the CA from finding the worst-case vehicular emissions under all demand scenarios (that is, when an uncertainty budget is not considered). Hence, the CA needs to determine the uncertainty budget to tradeoff computational burden and accuracy. Further, the uncertainty budget is higher for forecasts of travel demand rates further into the future, i.e. } U^t \geq U^{t-1} \text{ for any period } t. \text{ The demand uncertainty set also ensures that only one travel demand scenario is the worst-case demand scenario for each O-D pair in each time period. Then, the upper-level model is formulated as the following mathematical program:}
\]

\[
\min_{(u,n)} \max_{p} \sum_{t \in T} \sum_{a \in A} \nu_{a}^{t,2} e_{a}^{t}(\nu_{a}^{t}) \tag{3}
\]

\[
\frac{\mu_{w}^{t,m}}{\mu_{w}^{UE}} \leq \phi^{t} \quad \forall t, m, w \tag{4}
\]

\[
d \in \mathcal{E} \tag{5}
\]

where \(\phi^{t}\) denotes the maximum ratio of generalized travel cost after TCS implementation to the generalized travel cost \(\mu_{w}^{t,UE}\) without TCS (which is labeled as NoTCS) for any O-D pair in each period \(t\). The upper-level model (3)-(5) is a mixed-integer nonlinear mathematical program. The objective function (3) minimizes the maximum vehicular emissions rate that manifest under the possible travel demand scenarios. The decision variables in the upper-level are the vehicle type
specific O-D based credit allocation scheme and vehicle type specific link-based credit charging scheme.

As the CA aims to increase the market penetration of ZEVs, the worst-case vehicular emissions rate can be minimized, by allocating more credits to ZEV travelers and charging them fewer credits compared to ICEV travelers under the optimal plan. This increases the credit consumption costs of ICEV travelers, motivating travelers to shift to ZEVs. In the limit, this can imply that all travelers will shift to ZEVs within one period to minimize vehicular emissions rate. However, this is not sustainable in practice as substantial short-term increases in ICEV generalized travel costs are neither politically acceptable nor realistic from the perspective that all travelers will purchase ZEVs within a period. To account for realism in market behavior and to ensure that ICEV travel cost increases are within acceptable norms, the CA seeks to increase ICEV credit consumption costs gradually through the planning horizon so that travelers can better adapt to the multi-period TCS. Hence, to prevent significant increases in travel costs after TCS implementation, there is need for a constraint in the upper level to bound the generalized travel costs after TCS implementation compared to the ones under NoTCS. The generalized travel costs under NoTCS, $\mu_{w}^{L,UE}$, are the travelers’ costs before TCS implementation, and are used to assess the impact of TCS on travelers’ costs. They are the travel time costs under user equilibrium (UE) condition without TCS implementation and can be calculated using the mathematical program (26)-(28) in section 4. Constraints (4) state that the ratio of generalized travel cost after TCS implementation to the one under NoTCS for each O-D pair in each time period should not exceed the CA-specified ratio $\phi^t$. The CA can gradually increase $\phi^t$ during the planning horizon to motivate travelers to shift to ZEVs while ensuring that they adapt to TCS implementation in a sustainable manner.
Constraint (5) includes a set of binary constraints and states that the travel demand scenario should belong to travel demand uncertainty set \( \Xi \).

3.2. Lower-level model

This section describes the lower-level model in which travelers minimize their generalized travel costs under the TCS parameters determined in the upper level, through their vehicle type and route choices. Based on the multi-period TCS parameters obtained in the upper level, travelers change their routes and vehicle types to minimize their generalized travel costs. This process continues until no traveler is able to reduce his/her cost by unilaterally changing route and vehicle type, which is the multi-period equilibrium condition. Given the multi-period TCS \((n, u)\), the multi-period equilibrium condition can be formulated as the following mathematical model with complementarity constraints (MPCC):

\[
0 \leq \left( \sum_{a \in A} \left( (\alpha^c c_a^c(v_a^t + p^t u_a^{t,m}) \delta_{a,r,w} - \mu_{w}^{t,m} \right) \right) \perp f^{t,m}_{r,w} \geq 0 \quad \forall r, w, t, m \tag{6}
\]

\[
\sum_{j=2}^{T} z^{1,j} + \sum_{m \in M} \sum_{a \in A} u_a^{1,m} v_a^{1,m} = \xi^1 \tag{7}
\]

\[
\sum_{j=t+1}^{T} z^{t,j} + \sum_{m \in M} \sum_{a \in A} u_a^{t,m} v_a^{t,m} = \xi^t + \sum_{j=1}^{t-1} z^{j,t} \quad 1 < t < T \tag{8}
\]

\[
\sum_{m \in M} \sum_{a \in A} u_a^{T,m} v_a^{T,m} + Y^T = \xi^T + \sum_{j=1}^{t-1} z^{j,T} \tag{9}
\]

\[
0 \leq (p^t - y^{t,t'}) \perp z^{t,t'} \geq 0 \quad \forall t < T, \forall t < t' \tag{10}
\]

\[
0 \leq p^T \perp Y^T \geq 0 \tag{11}
\]
where \( p^t \) is the equilibrium credit price in period \( t \). Perpendicular operator \( \perp \) means that, vectors \( x \perp y = 0 \) if and only if \( x^T y = 0 \). Complementarity constraints (6) state that, in each period \( t \) at equilibrium, the generalized travel cost of vehicle type \( m \) on route \( r \) for O-D pair \( w \) with positive flow rate, \( f_{r,w}^{t,m} > 0 \), must be equal to the minimum generalized travel cost for that vehicle type and O-D pair, that is \( \mu_{w}^{t,m} \). Further, they state that the generalized travel cost of each vehicle type \( m \) for O-D pair \( w \) on route \( r \) is greater than or equal to \( \mu_{w}^{t,m} \) in time period \( t \). Constraint (7) states that the issued credit rate in the first period is equal to the sum of credit consumption and transfer rates to the future periods. Constraints (8) state that sum of credit consumption rate in the current period and credit transfer rate to the future periods is equal to the credit supply rate, i.e., sum of issued credit rate in the current period and credit transfer rates from previous periods. Constraint (9) states that the sum of credit discarding and consumption rates is equal to the credit supply rate in the last period where \( Y^T \) denotes the discarding rate of credits in the last period. Constraints (10) state that the credit price information of period \( t' > t \) in period \( t \) is less than or equal to the credit price in period \( t \). Constraints (10) also state that if credits are transferred from period \( t \) to period \( t' \), then the credit price information of period \( t' \) in period \( t \) is equal to the multi-period equilibrium credit price of period \( t \).

Constraint (11) states that if travelers discard credits in the last period, the multi-period equilibrium credit price of the last period \( T \) is equal to zero. In other words, unused credits are discarded at the end of the last period without monetary gains. Constraints (12) determine the
choice of ZEVs and ICEVs in each period using a binomial logit function. In this function, the adoption of ZEVs depends on the utility of ZEVs and ICEVs, where the deterministic component of the utility function consists of: (i) the monetary benefits under TCS, i.e. \( (p^t n_w^{t,m} - \mu_w^{t,m}) \), and (ii) the extra cost \( \lambda_w^{t,1} \) for ZEV travelers compared to ICEV travelers where this parameter is zero for ICEV travelers, i.e. \( \lambda_w^{t,2} = 0 \). The extra cost for ZEV travelers, \( \lambda_w^{t,1} \), can be determined in practice based on several factors such as initial purchase cost of ZEVs and the availability of refueling station locations. For example, the extra cost due to the higher initial purchase cost can be set equal to the difference in purchase costs of a ZEV and an ICEV divided by the number of trips by the ZEV over its lifetime. The extra cost due to the lack of availability of refueling stations can be obtained using the method proposed by He et al. (2013); they use the density of refueling stations, i.e. number of refueling stations divided by the areas of trip origin and destination, as an indicator for the availability of refueling stations for each O-D pair. Given the aggregate travel demand rate \( d \) and the equilibrium credit prices \( p = \{p^t, \forall t\} \), MPCC (6)-(13) can be reformulated as the following optimization problem:

\[
\min_{(v,q,z,B)} \sum_{t \in T} (\alpha^t \sum_{a \in A} \int_0^{y_a^t} c_a^t(\omega) d\omega + \sum_{t < t'} (p^t - r^{t,t'}) z^{t,t'} + \sum_{w \in W} \sum_{m \in M} q_w^{t,m} (\lambda_w^{t,m} - p^t n_w^{t,m}) + (\ln q_w^{t,m} - 1))
\]

(7)-(14)

It can be proved that the mathematical program (7)-(13) is identical to MPCC (6)-(13), where the Lagrangian multipliers for credit conservation constraints (7)-(9) are identical to the equilibrium credit prices. With the assumed properties of the link travel time functions and
credit price uniqueness, the objective function \((14)\) and constraints \((7)-(9),(13)\) are convex in link flows. Hence, it yields unique optimal link flows.

### 3.3. Robust Design of Multi-Period TCS: Bi-level Model

This section presents the RDMPTCS as a bi-level model. The bi-level model consists of the upper-level model presented in section 3.1 and lower-level model presented in section 3.2. The RDMPTCS is formulated as a mathematical program with equilibrium constraints (MPEC):

\[
\min_{(u,n)} \max_{(v,z,u,y)} \sum_{t \in T} \sum_{a \in A} v_t^2 e_t^a (v_t^a) \tag{15}
\]

\((4)-(5)\)

\((6)-(13)\)

As discussed earlier, the MPEC \((4)-(13),(15)\) is the bi-level model where the upper level model includes objective function \((15)\) and constraints \((4)-(5)\). The lower level model includes the MPCC \((6)-(13)\) in which travelers minimize their generalized travel costs under multi-period TCS parameters determined in the upper level. Because the CA aims to minimize the worst-case vehicular emissions rate by promoting ZEVs, ZEV travelers receive higher allocated credits and are charged fewer credits compared to ICEV travelers under the optimal plan. Consequently, ZEV travelers can gain monetary benefits by selling unused credits to ICEV travelers which further reduces their disutility. This provides a sustainable behavioral mechanism for travelers to shift toward ZEVs which is synergistically consistent with the CA’s goal of minimizing worst-case vehicular emissions rate. The MPEC \((4)-(13),(15)\) is a mixed-integer nonlinear model, and is
hence a NP-hard problem. The next section develops a solution algorithm to solve the MPEC \((4)-(13), (15)\) and determines the robust multi-period TCS parameters.

4. Solution Algorithm

This section presents a solution algorithm for the RDMPTCS by solving the MPEC \((4)-(13), (15)\). One method to solve MPEC \((4)-(13), (15)\) is the enumeration method in which possible demand scenarios are identified. Then, the RDMPTCS is determined by reformulating MPEC \((4)-(13), (15)\) to solve for the set of possible demand scenarios \(\mathcal{E}\). Let \(\phi\) denote the maximum vehicular emissions rate under the possible demand scenarios. Then, the MPEC \((4)-(13), (15)\) is reformulated as the following mathematical program:

\[
\min_{(u,p,n,v,\mu,y)} \phi
\]

\[
\sum_{t \in T} \sum_{a \in A} v_a^{t,d} e_a^t (v_a^{t,d}) \leq \phi \quad \forall d \in \mathcal{E}
\]

\[
\frac{\mu_w^{t,m,d}}{\mu_w^{t,d}} \leq \phi^t \quad \forall w, t, m, \forall d \in \mathcal{E}
\]

\[
0 \leq \left( \sum_{a \in A} \left( \alpha^t c^t_a (v_a^{t,d}) + p^t u_a^{t,m} \delta_{a,r,w} \right) - \mu_w^{t,m,d} \right) \perp f_{r,w}^{t,m,d} \geq 0 \quad \forall r, w, t, m, \forall d \in \mathcal{E}
\]

\[
\sum_{j=2}^{T} z_{j,d} + \sum_{m \in M} \sum_{a \in A} u_a^{1,m} v_a^{1,m,d} = \xi^1 \quad \forall d \in \mathcal{E}
\]

\[
\sum_{j=t+1}^{T} z_{j,d} + \sum_{m \in M} \sum_{a \in A} u_a^{t,m} v_a^{t,m,d} = \xi^t + \sum_{j=1}^{t-1} z_{j,d} \quad \forall d \in \mathcal{E}, 1 < t < T
\]

\[
\sum_{m \in M} \sum_{a \in A} u_a^{T,m} v_a^{T,m,d} + 2T = \xi^T + \sum_{j=1}^{t-1} z_{j,T,d} \quad \forall d \in \mathcal{E}
\]
\[ 0 \leq (p_{t,d} - \gamma^{t,t'}) \perp z^{t,t'} \geq 0 \quad \forall d \in \Xi, \forall t < T, \forall t' \] (23)

\[ 0 \leq p^{T,d} \perp \gamma^{T,d} \geq 0 \quad \forall d \in \Xi \] (24)

\[ q_{t,m,d} = \frac{d^{t}_{w,e}(\sigma_{t,d} n_{w,m}^{t} - \mu_{w,m}^{t,d} - \lambda_{w,m})}{\sum_{m \in M} e(\sigma_{t,d} n_{w,m}^{t} - \mu_{w,m}^{t,d} - \lambda_{w,m})} \quad \forall w, m, t, \forall d \in \Xi \] (25)

where the superscript \( d \) denotes variables associated with a particular demand rate \( d \in \Xi \). The objective function (16) minimizes the maximum vehicular emissions rate \( \varphi \). Constraints (17) state that vehicular emissions rates under possible demand scenarios are less than or equal to \( \varphi \).

Constraints (18) and (19)-(25) are identical to constraints (4) and (6)-(12) for possible demand scenarios, respectively. For constraints (18), the minimum generalized travel costs \( \mu^{UE} = \{\mu_{w}^{t,UE}, w \in W, t \in \Gamma\} \) can be determined for a given demand rate \( d \) under the UE condition without TCS by solving the following MPEC:

\[ 0 \leq (\alpha^{t} \sum_{a \in A} (c_{a}^{t}(v_{a}^{t}) \delta_{a,r,w}) - \mu_{w}^{t,UE}) \perp f_{r,m}^{t} \geq 0 \quad \forall r, w, t, m \] (26)

\[ q_{w,m}^{t,m} = \frac{d^{t}_{w,e}(\mu_{w}^{t,UE} - \lambda_{w,m})}{\sum_{m \in M} e(\mu_{w}^{t,UE} - \lambda_{w,m})} \quad \forall m, w, \forall t \] (27)

\( (f^{M}, v^{M}, \nu) \in \Omega(d) \) (28)

Complementarity constraints (26) represent the UE condition without TCS, and state that the travel times of the utilized paths for each O-D pair are less than or equal to the minimum travel time for that O-D pair. Constraints (27) specify the travelers’ vehicle type choices under the equilibrium condition. Constraint (28) is identical to constraint (13). In practice, although the number of
demand scenarios is finite, MPEC((13),(16)-(25)) is computationally expensive to solve due to the large number of possible demand scenarios. It contains three sets of complementarity constraints which are difficult to solve, especially for a large set of demand scenarios.

To solve MPEC((13),(16)-(25)), we adopt a cutting plane method (Lawphongpanich and Hearn, 2004) which has been used previously in traffic network design studies (Lou et al., 2009). In this method, the problem is divided into two subproblems. In the first subproblem, we obtain TCS parameters which minimize the maximum vehicular emissions rate under the demand scenarios of a subset \( \tilde{\mathcal{S}} \subseteq \mathcal{S} \) with a smaller set of demand scenarios. To update subset \( \tilde{\mathcal{S}} \), the second subproblem is solved to generate a new demand scenario, that leads to higher vehicular emissions rate compared to the current solution, and update \( \tilde{\mathcal{S}} \). After updating \( \tilde{\mathcal{S}} \), the first subproblem is solved again and this iterative procedure is continued until no new demand scenario is available to update \( \tilde{\mathcal{S}} \).

As the first subproblem, MPEC((13),(16)-(25)) is relaxed to solve for a smaller subset \( \tilde{\mathcal{S}} \). Then, the relaxed mathematical program (RMP) is formulated for a subset \( \tilde{\mathcal{S}} \subseteq \mathcal{S} \) as follows:

\[
\begin{align*}
\min_{(u,p,n,v,z,\theta)} & \quad \theta \\
\text{s.t.} & \quad (17)-(25), (13) \\
& \quad \forall d \in \tilde{\mathcal{S}}
\end{align*}
\]  

The program RMP is identical to the MPEC((13),(16)-(25)) except that it is solved for a subset of demand scenarios. Let \((\tilde{u}, \tilde{n}, \tilde{\theta})\) be an optimal solution to RMP. \((\tilde{u}, \tilde{n}, \tilde{\theta})\) solves MPEC((13),(16)-(25)) if and only if the vehicular emissions rate of every demand rate \(d \in \mathcal{S}\) is less than or equal to \(\tilde{\theta}\) under the multi-period TCS design \((\tilde{u}, \tilde{n})\). If the travel demand uncertainty
subset $\tilde{\mathfrak{S}}$ only includes the average aggregate travel demand rate $d_w^{t,1}$, then RMP reduces to the system optimal design of multi-period TCS (SOMPTCS) in which the CA aims to minimize vehicular emissions rate under the average aggregate travel demand rate. The SOMPTCS will be used in numerical experiments in section 5.1 as benchmark to compare the performance of RDMPTCS, and to illustrate the importance of factoring travel demand uncertainty for achieving effective and reliable TCS design.

The second subproblem generates a new demand scenario that may lead to higher vehicular emissions rate, resulting in the update of $\tilde{\mathfrak{S}}$. Given $(\hat{u}, \hat{n})$, the maximum vehicular emissions rate is obtained by solving the following MPEC:

$$\max_{(v, x, y, r, p, d)} \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A}} v_{a}^{t,2} e_{a}^{t}(v_{a}^{t})$$

$$0 \leq \left(\sum_{a \in \mathcal{A}} ((\alpha^t c_a(v_a^t) + p^t \hat{u}_a^{t,m} - \mu_w^{t,m}) - \mu_w^{t,m}) \perp f_{r,w}^{t,m} \right) \geq 0 \quad \forall r, w, t, m$$

$$\sum_{j=2}^{T} z_{j}^{t,j} + \sum_{m \in \mathcal{M}} \sum_{a \in \mathcal{A}} \hat{u}_a^{1,m} v_a^{1,m} = \xi^1$$

$$\sum_{j=t+1}^{T} z_{j}^{t,j} + \sum_{m \in \mathcal{M}} \sum_{a \in \mathcal{A}} \hat{u}_a^{t,m} v_a^{t,m} = \xi^t + \sum_{j=1}^{t-1} z_{j,t}$$

$$\sum_{m \in \mathcal{M}} \sum_{a \in \mathcal{A}} \hat{u}_a^{t,m} v_a^{t,m} + Y^T = \xi^T + \sum_{j=1}^{t-1} z_{j,T}$$

$$0 \leq (p^t - \hat{p}^{t,t'}) \perp z^{t,t'} \geq 0 \quad \forall t < T, \forall t < t'$$

$$q_{w,m}^{t} = \frac{d_{w}^{t} e(p_{w}^{t,m} - \mu_{w}^{t,m} - \lambda_{w}^{t,m})}{\sum_{m \in \mathcal{M}} e(p_{w}^{t,m} - \mu_{w}^{t,m} - \lambda_{w}^{t,m})} \quad \forall w, m, t$$
The MPEC ((5),(11),(13),(31)-(37)) is difficult to solve because it is a mixed-integer nonlinear program with complementarity constraints. To solve, it is divided into two subproblems following the approach proposed by Lou et al. (2009). The first subproblem solves the MPEC ((5),(11),(13),(31)-(37)) for a given demand scenario and the second subproblem uses Lagrangian multipliers to find a new demand scenario that leads to a higher vehicular emissions rate. In the first subproblem, we define two sets, \( I_B \bar{d}^C = \{ (t,s,w) | \eta^{t,s}_w = 0 \} \) and \( I_R \bar{d}^C = \{ (t,s,w) | \eta^{t,s}_w = 1 \} \) for an initial demand rate, e.g. \( \bar{d} \). These sets are referred as active sets by Zhang et al. (2009) because they determine which of the two constraints, \( 0 \leq \eta^{t,s}_w \) or \( \eta^{t,s}_w \leq 1 \), is active or binding. Then, the MPEC ((5),(11),(13),(31)-(37)) can be relaxed as the following index-set-based optimization problem (ISBOP):

\[
\max_{(v,\eta,\alpha,\gamma,p,d,q)} \sum_{t \in T} \sum_{a \in A} v^t_a e^t_a (v^t_a) \quad (38)
\]

\[
\eta^{t,s}_w = 0 \quad \forall (t,s,w) \in I(\bar{d}) \quad (39)
\]

\[
\eta^{t,s}_w = 1 \quad \forall (t,s,w) \in I^C(\bar{d}) \quad (40)
\]

The second subproblem generates a new demand scenario. To do so, a knapsack problem is formulated using the Lagrangian multipliers of constraints (39) and (40) to determine whether changing the values of \( \eta \) can increase the objective function (38). Let \( \bar{m}^{t,s}_w \) and \( \bar{p}^{t,s}_w \) denote the
Lagrangian multipliers associated with constraints (39) and (40), respectively. Lou et al. (2009) suggest to update $I(\bar{d})$ and $I^c(\bar{d})$ using the following mixed-integer knapsack problem (MIKP):
generate another demand scenario that leads to a higher vehicular emissions rate. To do so, initially set auxiliary variable \( \theta = \infty \), and then if the newly generated demand scenario reduces vehicular emissions \( \theta \), set \( \theta \) to be equal to \( \theta - \delta \) where \( \delta \) is a sufficiently small positive number. This forces MIKP to generate another demand scenario.

The solution algorithm for solving MPEC((13),(16)-(25)) is shown in Fig. 2. Lou et al. (2009) discuss that this solution algorithm will terminate after a finite number of iterations since the travel demand uncertainty set includes a finite number of demand scenarios. Hence, the convergence of this algorithm to the optimal solution is guaranteed.

**Fig. 2.** Flowchart of solution algorithm for solving MPEC((13),(16)-(25))
5. Numerical Experiments

In this section, numerical experiments are conducted using the Sioux-Falls network with 24 nodes, 76 links and 552 O-D pairs. The Sioux-Falls network is represented in Fig. 3. Detailed characteristics of the network including free flow travel times, and link capacity can be found in LeBlanc et al. (1975). In the numerical experiments, we use carbon monoxide (CO) as an indicator for vehicular emissions. This is due to three reasons. First, the vehicular emissions are the main source of CO emissions (Yin and Lawphongpanich, 2006). Second, CO is one of the most important pollutants among various vehicular emissions type (Alexopoulos et al., 1993; Xu et al., 2015). Hence, it is expected that if the emissions functions of other pollutants are incorporated into the model, the results should not change significantly. Third, the emissions functions of other pollutants are similar to that of CO (Hizir, 2006; Li et al., 2012; Nagurney et al., 2010). Therefore, this function has been used in various studies (e.g. Ma et al., 2017, 2015; Xu et al., 2015; Yang et al., 2017, 2014). Wallace et al. (1998) formulate the CO emissions function \( e_a^t(v_a^t) \) (in g/veh) of link \( a \) in period \( t \) as follows:

\[
e_a^t(v_a^t) = 0.2038c_a^t(v_a^t) \cdot \exp \left( \frac{0.7962l_a^t}{c_a^t(v_a^t)} \right) \quad \forall a, \forall t
\]  

(46)

where \( l_a^t \) is the length (in kilometers) and \( c_a^t(v_a^t) \) is the travel time (in minutes) of link \( a \) in period \( t \). This CO emissions function have been used in several studies that aims to mitigate vehicular emissions (e.g. Ma et al., 2017, 2015; Xu et al., 2015; Yang et al., 2017, 2014). As traffic flow consists of two vehicle types, ZEVs and ICEVs, and only the second vehicle type is the source of CO emissions, \( e_a^t(v_a^t) \) represents the emissions rate of only ICEVs.
The planning horizon is divided into five periods where the duration of each period is equal to 5 years. To capture the travel demand uncertainty, three potential demand scenarios, including low \( d^{t,1}_w \), average \( d^{t,2}_w \) and high \( d^{t,3}_w \), are considered for each O-D pair. The travel demand of LeBlanc et al. (1975) is used as average demand rate for the first period. The average travel demand rates for the successive periods are calculated based on the constant growth rate \( r \). In other words, the average travel demand for period \( t > 1 \) is equal to \((1 + r)^{t-1}d^{1,2}_w\). The low and high travel demand scenarios are generated based on the average travel demand rate using the following equation:

\[
d^{t,s}_w = (\theta^s)d^{t,2}_w \quad s = 1,3
\]  

where \( \theta^s \) is the parameter controlling the level of uncertainty for scenario \( s \) and \( r \) is the constant growth rate of the aggregate travel demand rate during the planning horizon. The link travel times are assumed to follow the traditional bureau of public roads (BPR) delay function. The value of
time, predetermined bound on increase in generalized travel cost $\phi^t$, and the parameters controlling the level of uncertainty $\theta^s$ for scenario $s$ and the extra cost of ZEV travelers $\lambda^s_{w}$ (in $\$$) are as shown in Table 1 unless stated otherwise. The values of time through the planning horizon are in the range of 20-24 ($$/hr) following the values suggested by FHWA (2016). Further, since Yin (2017) suggests that the annual demand growth rate in Shanghai is equal to 1.6% and each period of our study is of the order of 5 years, the growth demand rate is equal to 8.2%, that is $(1 + 0.016)^5 - 1)$. In this study, we assume that it is equal to 10% unless stated otherwise. The other values in Table 1 are primarily for illustrative purpose.

The optimization software package GAMS is used to solve the model on one cluster node with four 2.3-GHz 12-core AMD Opteron 6176 processors, and 192 GB RAM per node. The model has about 8640 binary variables and about 61,000 constraints. The CPU time to solve for the RDMPTCS is approximately 51,000 seconds. While the solution algorithm can be perceived as inefficient, it is reasonable given the multi-year planning context of the proposed robust TCS design. In future studies, more efficient solution algorithms need to be developed to improve the efficiency of solving for the robust TCS design.

**Table 1**

<table>
<thead>
<tr>
<th>Time period</th>
<th>$\phi^t$</th>
<th>$\lambda^t_{w}$</th>
<th>$r$</th>
<th>$\alpha^t$</th>
<th>$\theta^1$</th>
<th>$\theta^3$</th>
</tr>
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<td>1.1</td>
<td>2.00</td>
<td>0.1</td>
<td>20</td>
<td>0.8</td>
<td>1.2</td>
</tr>
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<td>1.96</td>
<td>0.1</td>
<td>21</td>
<td>0.8</td>
<td>1.2</td>
</tr>
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<td>1.91</td>
<td>0.1</td>
<td>22</td>
<td>0.8</td>
<td>1.2</td>
</tr>
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<td>23</td>
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<tr>
<td>5</td>
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<td>1.76</td>
<td>0.1</td>
<td>24</td>
<td>0.8</td>
<td>1.2</td>
</tr>
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Section 5.1 compares the performance of SOMPTCS and RDMPTCS under travel demand uncertainty. Section 5.2 performs sensitivity analysis to understand the impacts of the extra costs for ZEV travelers and the bound on the increase in generalized travel costs across periods under the RDMPTCS.

5.1. Comparison of RDMPTCS and SOMPTCS

To compare the performance of SOMPTCS and RDMPTCS under travel demand uncertainty, we use Monte Carlo simulation and generate 500 samples of travel demand rates using the discrete uniform distribution. Thereby, the occurrence probabilities of each low, average, and high demand scenarios are 1/3 in each sample. The values of $\theta^*$ under low and high demand scenarios in equation (47) are equal to 0.8 and 1.2, respectively. In the RDMPTCS, the uncertainty budgets for the first, second, third, fourth and fifth periods are equal to 45, 50, 55, 60 and 65, respectively. Under each generated travel demand rate, the vehicular emissions under the SOMPTCS and RDMPTCS are determined. Then, the maximum, average and standard deviation of the 500 realized vehicular emissions under the RDMPTCS are compared with those under the SOMPTCS.

Fig. 4 illustrates the performance of SOMPTCS and RDMPTCS by plotting the realized vehicular emissions in the third and fifth periods, and realized vehicular emissions through the planning horizon under the generated travel demand scenarios. As shown in Table 3, under the SOMPTCS, the average vehicular emissions of the third and fifth periods are 44.06 $ktonnes^1$ and 8.44 $ktonnes$, respectively, with standard deviations of 1.24 and 0.51. The average realized

---

1 Kilotonnes
vehicular emissions through the planning horizon under SOMPTCS is equal to 178.06 ktonnes with standard deviation of 2.37. Under the RDMPTCS, the average vehicular emissions of the third and fifth periods are 39.29 ktonnes and 5.72 ktonnes, respectively, with standard deviations of 1.18 and 0.48. This suggests that the RDMPTCS leads to fewer vehicular emissions and lower volatility. The RDMPTCS also leads to lower average realized vehicular emissions (161.22 ktonnes) and standard deviation (2.30) through the planning horizon. Under the SOMPTCS, the maximum realized vehicular emissions through the planning horizon is 187.32 ktonnes, and for the third and fifth periods are 47.91 ktonnes and 10.20 ktonnes, respectively. By contrast, the maximum realized vehicular emissions through the planning horizon under the RDMPTCS reduces to 175.56 ktonnes, and those of the third and fifth periods to 43.50 ktonnes and 7.13 ktonnes, respectively. Hence, if the CA does not factor travel demand uncertainty in the TCS design, the SOMPTCS can lead to higher and more volatile realized vehicular emissions, preventing the CA from achieving predetermined system-level goals for each period in practice.
(a) Realized vehicular emissions of third period

(b) Realized vehicular emissions of fifth period

(c) Realized vehicular emissions through the planning horizon

Fig. 4. Realized vehicular emissions under SOMPTCS and RDMPTCS
Next, we investigate the performance of the RDMPTCS under different uncertainty budgets. Table 2 shows three uncertainty budget cases through the planning horizon. The uncertainty budget in each period is the lowest for case 1 and the highest for case 3. To evaluate the performance of RDMPTCS under the three uncertainty budget cases, Monte Carlo simulations are performed with 500 generated travel demand rates using the discrete uniform distribution. Table 3 illustrates the effect of uncertainty budget on the vehicular emissions rates in the third and fifth periods, and the vehicular emissions through the planning horizon under the three cases. It can be observed that the RDMPTCS under low (case 1), medium (case 2) and high (case 3) uncertainty budgets reduce the average realized vehicular emissions through the planning horizon by 6%, 9% and 24% compared to the SOMPTCS, respectively. The maximum realized vehicular emissions through the planning horizon reduce by 2%, 5% and 18% under RDMPTCS compared to the SOMPTCS, respectively, for the three cases. As the CA increases the uncertainty budget, the RDMPTCS results in the reduction of average, and maximum values of the realized vehicular emissions. A similar trend is observed for the vehicular emissions in the third and fifth periods. Hence, if the CA increases the uncertainty budget, the RDMPTCS can lead to more reliable TCS parameters to minimize vehicular emissions in practice.
Table 2

Uncertainty budget cases

<table>
<thead>
<tr>
<th></th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25</td>
<td>45</td>
<td>65</td>
</tr>
<tr>
<td>2</td>
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<td>4</td>
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<td>60</td>
<td>80</td>
</tr>
<tr>
<td>5</td>
<td>45</td>
<td>65</td>
<td>85</td>
</tr>
</tbody>
</table>

Table 3

Average, standard deviation and maximum realized vehicular emissions (in ktonnes)

<table>
<thead>
<tr>
<th>Realized vehicular emissions</th>
<th>Uncertainty budget case</th>
<th>SOMPTCS</th>
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<tbody>
<tr>
<td></td>
<td>Case 1</td>
<td>Case 2</td>
</tr>
<tr>
<td>Third period</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>40.48</td>
<td>39.29</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.18</td>
<td>1.18</td>
</tr>
<tr>
<td>Maximum</td>
<td>44.90</td>
<td>43.50</td>
</tr>
<tr>
<td>Fifth period</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>6.50</td>
<td>5.72</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.53</td>
<td>0.48</td>
</tr>
<tr>
<td>Maximum</td>
<td>8.28</td>
<td>7.13</td>
</tr>
<tr>
<td>Planning horizon</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>167.20</td>
<td>161.22</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>2.73</td>
<td>2.30</td>
</tr>
<tr>
<td>Maximum</td>
<td>183.68</td>
<td>175.56</td>
</tr>
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</table>

5.2. Sensitivity analysis

In this section, Monte Carlo simulations are conducted to perform sensitivity analysis to understand the effects of different parameters on market penetration rates and vehicular emissions.
under the RDMPTCS. 200 samples of travel demand rates are generated using the discrete uniform distribution to determine the realized travelers’ costs, ZEV market penetration rate and vehicular emissions. The market penetration rate of each vehicle class for each period is calculated as follows:

$$\eta^{t,m} = \frac{\sum_w q_w^{t,m}}{\sum_w d_w^t}, \quad \forall t, m$$ (48)

where $\eta^{t,m}$ denotes the market penetration of vehicle class $m$ in period $t$. This approach has been used in other studies (e.g. Chen et al. (2016) in the context of autonomous vehicles).

As before, the occurrence probabilities of low, average, and high demand scenarios are 1/3. The values of $\theta^S$ under low and high demand scenarios in equation (47) are equal to 0.8 and 1.2, respectively. The uncertainty budgets for the first, second, third, fourth and fifth periods are equal to 45, 50, 55, 60 and 65, respectively.

Fig. 5 illustrates the percentage of allocated credits to each vehicle type, and the average extra travel costs of ZEV and ICEV travelers under the RDMPTCS compared to the NoTCS case. Fig. 5(a) illustrates that the percentages of allocated credits to ICEV and ZEV travelers decrease and increase, respectively, during the planning horizon. This is because as the maximum ratio of generalized travel costs under RDMPTCS to that under NoTCS increases through the planning horizon, the CA allocates more credits to ZEV travelers. As the CA allocates credits more to ZEV travelers, they can gain monetary benefit, and hence experience lower costs compared to the NoTCS case. By contrast, ICEV travelers have to purchase credits to meet their travel needs, and consequently experience higher costs under the RDMPTCS compared to the NoTCS case. During periods 3-5, the CA can implement TCS with lesser extra cost imposed on ICEV travelers. This is
because the extra cost of ZEV travelers $\lambda^{t,1}_w$ reduces significantly until these periods due to technological advancements, providing an incentive for travelers to shift towards ZEVs. This leads to a reduction in ICEV travel demand. Hence, the CA does not need to increase TCS-related cost on ICEV travelers. Consequently, the travel cost of ICEV travelers reduces over periods 3-5. Although the monetary benefits of ZEVs reduce over periods 3-5, their market penetration rate increases through the planning horizon (Fig. 5(b)). This is because their extra costs reduce over the planning horizon due to technological advancements (Table 1) which motivates ICEV travelers to shift to ZEVs.

![Graph](image-url)  
(a) Percentage of allocated credits

![Graph](image-url)  
(b) Extra cost for ZEV/ICEV travelers compared to the NoTCS case

**Fig. 5.** Percentage of allocated credits and extra cost of ZEV/ICEV travelers under RDMPTCS compared to NoTCS.
Next, sensitivity analysis is performed to understand the effect of the extra cost of ZEV travelers under RDMPTCS on the vehicular emissions and market penetration rate through the planning horizon. Table 4 shows the values of the extra cost for ZEV travelers under four cases; this cost increases from case 1 to case 4 for each period.

**Table 4**

Four cases of the extra cost of using ZEVs in different periods ($)

<table>
<thead>
<tr>
<th>Time period</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>1.33</td>
<td>1.26</td>
<td>1.17</td>
<td>1.07</td>
<td>0.96</td>
</tr>
<tr>
<td>Case 2</td>
<td>2.00</td>
<td>1.96</td>
<td>1.91</td>
<td>1.84</td>
<td>1.76</td>
</tr>
<tr>
<td>Case 3</td>
<td>2.67</td>
<td>2.66</td>
<td>2.64</td>
<td>2.61</td>
<td>2.56</td>
</tr>
<tr>
<td>Case 4</td>
<td>3.33</td>
<td>3.36</td>
<td>3.37</td>
<td>3.37</td>
<td>3.36</td>
</tr>
</tbody>
</table>

Fig. 6 plots the average realized vehicular emissions and market penetration rates of ZEVs under different extra costs of ZEV travelers through the planning horizon. Fig. 6(a) illustrates that for each period, the realized vehicular emissions increases as the extra cost of ZEV travelers increases; hence, the realized vehicular emissions are the highest for case 4. This is because the market penetration rate of ZEVs reduces as its extra cost increases from case 1 to case 4 (Fig. 6(b)). As can be observed from equation (47), the aggregate travel demand rate increases at the constant growth rate 0.1 through the planning horizon. Hence, the average vehicular emissions increases during periods 1 and 2 under the RDMPTCS in cases 3 and 4. However, the average vehicular emissions reduce after period 2 under the RDMPTCS in these cases as the CA gradually
increases ICEV travelers’ consumption costs, which motivates more travelers to shift to ZEV. Consequently, the realized market penetration of ZEVs increases through the planning horizon (Fig. 6(b)). Finally, it can be observed that if the extra cost of ZEV travelers is lower, the multi-period TCS leads to a significant reduction in the vehicular emissions during the planning horizon. This suggests that technological advances in ZEVs and higher availability of charging stations enhance the effectiveness of a multi-period TCS as the extra cost of ZEV travelers reduce.

![Graph of realized vehicular emissions and ZEV market penetration rate](image.png)

**Fig. 6.** Realized vehicular emissions and ZEV market penetration rate under different cases of extra cost of ZEV travelers.
Table 5

Maximum ratio of generalized travel cost under TCS to that under NoTCS

<table>
<thead>
<tr>
<th>Time period</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.1</td>
<td>1.4</td>
<td>1.7</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>1.2</td>
<td>1.5</td>
<td>1.8</td>
<td>2.1</td>
</tr>
<tr>
<td>3</td>
<td>1.3</td>
<td>1.6</td>
<td>1.9</td>
<td>2.2</td>
</tr>
<tr>
<td>4</td>
<td>1.4</td>
<td>1.7</td>
<td>2</td>
<td>2.3</td>
</tr>
<tr>
<td>5</td>
<td>1.5</td>
<td>1.8</td>
<td>2.1</td>
<td>2.4</td>
</tr>
</tbody>
</table>

The sensitivity analysis is performed to understand the effect of the maximum ratio of generalized travel cost under RDMPTCS compared to the one under NoTCS. Table 5 shows four cases of the maximum ratio, which increases from case 1 to case 4 for each period. Fig. 7 illustrates the average realized vehicular emissions and ZEV market penetration rates for four cases of the maximum ratio of the generalized travel costs under RDMPTCS to that under NoTCS. The vehicular emissions are lower under RDMPTCS than for the NoTCS case due to the higher ZEV market penetration rates and the changes in travelers’ route choices. Also, when the RDMPTCS is implemented with increasing maximum ratios from case 1 to case 4 in each period, it implies that ICEV generalized costs increases can be higher across consecutive periods, leading to increased ZEV adoption across periods and higher reductions in vehicular emissions as shown in Fig. 7(a). Also, as shown in Fig. 7(b), the ZEV market penetration rates are the highest for case 4 as it allows the most increases in ICEV generalized travel costs leading to a higher shift to ZEVs in this case compared to the other three cases. Also, it can be observed that if the CA designs the RDMPTCS with a low bound on the increase in generalized travel costs (e.g. case 1), then the multi-period TCS cannot achieve significant reductions in the vehicular emissions through the planning horizon.

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This suggests that the CA needs to tradeoff the effectiveness of the RDMPTCS to reduce vehicular emissions and the increase in generalized travel costs after TCS implementation, to enable TCS sustainability in practice.

**Fig. 7.** Vehicular emissions and ZEV market penetration rates for different cases of the maximum ratio
In addition to travel demands, there can be uncertainty in the long-term forecasts of other parameters of robust TCS design such as value of time and travel demand growth rate. We conduct sensitivity analysis to understand the impacts of various values of time and travel demand growth rates. Fig. 8 presents the vehicular emissions and market penetration rates under four different values of time. The values of time under cases 1, 2, 3, and 4 are assumed to be equal to 15, 20, 25 and 30 $/hr, respectively. Since the TCS-related costs of ICEV travelers increase and the extra costs of using ZEVs due to technological advancements decrease, the market penetrations of ZEVs increases under all cases during the planning horizon. This helps the CA to promote ZEVs and reduce vehicular emissions during the planning horizon. The market penetration rates are highest under case 4 and hence, vehicular emissions are lower under it compared to cases 1-3. This is because the value of time is a proxy for travelers’ income. Hence, travelers with higher value of time are more likely to afford ZEVs which have higher initial purchase cost. This leads to increase of ZEV market penetration and reduction of vehicular emissions through the planning horizon. This suggests that by improving the state of the economy which leads to higher social welfare, travelers are more willing to purchase ZEVs and this further helps the CA to achieve environmentally sustainable transportation system.
Fig. 8. Vehicular emissions and ZEV market penetration rates under different values of time.
The travel demand growth rate is another parameter with inherent uncertainty over the long planning horizon. To understand the impact of its forecast on robust TCS design, we conduct a sensitivity analysis under four cases ($r = 0.05, 0.1, 0.13, 0.3$) which is shown in Fig. 9. When travel demand growth rate is 0.05, the vehicular emissions are lesser compared to other cases due to lesser trips through the planning horizon. As the travel demand growth rate increases, the higher traffic congestion leads to higher travel costs for travelers which further motivate travelers to shift toward ZEV to receive monetary incentive. Hence, the ZEV market penetration rates are highest and lowest when the travel demand growth rates are equal to 0.3 and 0.05, respectively. Despite the higher ZEV market penetration, the vehicular emissions are higher compared to other cases in the second period when the travel demand growth rate is equal to 0.3. This is due to the higher number of ICEV trips in traffic network. However, as ZEV market penetration rate increases, the vehicular emissions become lesser compared to other cases when the travel demand growth rate is equal to 0.3. This suggests that as traffic congestion increases in traffic network, the TCS implementation becomes more effective in motivating travelers to purchase ZEVs which leads to reduction of vehicular emissions.
Fig. 9. Vehicular emissions and ZEV market penetration rates under different travel demand growth rates.
6. Concluding Comments

This study proposes a novel hybrid transportation emissions reduction approach in which a CA leverages a multi-period TCS to develop an incentive mechanism to achieve system-level goals by sustainably promoting the usage of ZEVs (e.g. Battery electric and hydrogen vehicles). The multi-period TCS based approach circumvents the need for expensive price subsidies from the CA to promote ZEVs. As the CA allocates more credits to ZEV travelers and charges them fewer credits to travel on links under the designed multi-period TCS, ZEV travelers can sell unused credits in the market and accrue monetary benefits. This enhances their utility of the ZEV and fosters a sustainable behavioral mechanism to shift to and/or continue to use ZEVs.

Due to the uncertainty in forecasting future travel demand over a long-term planning horizon in the order of several years, the study proposes a robust multi-period TCS design, formulated as a min-max bi-level mathematical program. In the upper level, the CA seeks to optimize the TCS parameters for the worst-case vehicular emissions that manifest under a travel demand uncertainty set. The travel demand uncertainty set consists of a finite number of possible travel demand scenarios. Since the number of scenarios can be very large, an uncertainty budget is proposed to mitigate the computational burden, in which a certain number of O-D travel demand rates can deviate from their average values. While the uncertainty budget reduces the computational cost, it can preclude obtaining the worst-case vehicular emissions under all demand scenarios. Hence, the use of an uncertainty budget provides the CA a practical mechanism to tradeoff computational cost and accuracy. The lower-level model determines the equilibrium condition under the multi-period TCS, in which travelers minimize their generalized travel costs based on the multi-period TCS parameters obtained in the upper level. A binomial logit model is used to capture the choice of
ZEV and ICEV travelers. The cutting-plane method is used to solve for the robust multi-period TCS design.

Results of numerical experiments illustrate that ZEV travelers sell their credits in the market and make monetary gains that reduce their costs under the RDMPTCS compared to the NoTCS case. This leads to an increase in ZEV market penetration and a reduction in vehicular emissions over the planning horizon, thereby addressing the CA’s system-level goals. Further, accounting for travel demand uncertainty using the RDMPTCS generates performance gains as the maximum and average realized vehicular emissions under the travel demand scenarios generated in the experiments are lower compared to those under the SOMPTCS. The study insights suggest that the CA can leverage a multi-period TCS as an effective market-based instrument to enhance ZEV usage. As the extra cost of using ZEV reduces with technological advances and increased infrastructure over time, the RDMPTCS can become even more effective in reducing vehicular emissions through the planning horizon. Finally, the RDMPTCS reduces volatility in vehicle emission rates compared to the design based on deterministic travel demand.

This study can be extended in a few directions. First, beyond the ZEV and ICEV, vehicles can be classified according to their emission levels to design a RDMPTCS with vehicle type specific credit allocation and charging schemes. Second, the proposed RDMPTCS can potentially be inequitable if the cost to purchase a ZEV is high, and further ZEV users benefit from selling credits the market. While ZEV costs are progressively decreasing, another approach is to incorporate equity constraints into the TCS design whereby the CA provides incentives based on the traveler’s income. Third, this study assumes that value of time is identical for all travelers. However, in reality, travelers are heterogeneous in terms of value of time, which impacts both the route and
vehicle choices of travelers. Hence, a future research direction is to capture the impact of travelers’ heterogeneity in terms of value of time on route and vehicle choices. Fourth, this study assumes that the CA has perfect information on travelers’ value of time through the long-term planning horizon. However, there is an uncertainty associated with such forecasts that needs to be captured. Fifth, this study captures the share of ZEVs and ICEVs using a binomial logit function for each O-D pair, which assumes that the travel demands of O-D pairs are independent. Hence, it does not address the travel demand at the household level which can have dependency. This assumption needs to be relaxed so as to capture the household vehicle choice after TCS implementation. Finally, it would be useful to explore a more efficient solution algorithm for the proposed robust TCS design which contains one set of integer variables $\eta_{w}^{l}$, three sets of complementarity constraints \((6),(10),(11)\) and one set of nonlinear constraints \((12)\). Although the cutting-plane scheme adopted in this study can solve for the robust TCS design for the Sioux-Falls network, it needs to be improved to solve for the robust TCS design for large-scale networks. Potential improvements can involve leveraging the Benders decomposition method (Varsei and Polyakovskiy, 2017) to solve the MIKP and the gap function (Xu et al., 2015) to solve the MPCC \((6)-(13)\) with complementarity and nonlinear constraints.

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7. References


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