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# A quantitative and systematic methodology to investigate energy consumption issues in multimodal intercity transportation systems

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## ABSTRACT

Energy issues in transportation systems have garnered increasing attention recently. This study proposes a systematic methodology for policy-makers to minimize energy consumption in multimodal intercity transportation systems considering suppliers' operational constraints and travelers' mobility requirements. A bi-level optimization model is developed for this purpose and considers the air, rail, private auto, and transit modes. The upper-level model is a mixed integer nonlinear program aiming to minimize energy consumption subject to transportation suppliers' operational constraints and traffic demand distribution to paths resulting from the lower-level model. The lower-level model is a linear program seeking to maximize the trip utilities of travelers. The interactions between the multimodal transportation suppliers and intercity traffic demand are considered under the goal of minimizing system energy consumption. The proposed bi-level mixed integer model is relaxed and transformed into a mathematical program with complementarity constraints, and solved using a customized branch-and-bound algorithm. Numerical experiments, conducted using multimodal travel options between Lafayette, Indiana and Washington, D.C. reiterate that shifting traffic demand from private cars to the transit and rail modes significantly reduce energy consumption. Moreover, the proposed methodology provides tools to quantitatively analyze system energy consumption and traffic demand distribution among transportation modes under specific policy instruments. The results illustrate the need to systematically incorporate the interactions among traveler preferences, network

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structure, and supplier operational schemes to provide policy-makers insights for developing traffic demand shift mechanisms to minimize system energy consumption. Hence, the proposed methodology provide policy-makers the capability to analyze energy consumption in the transportation sector by a holistic approach.

**Keywords:** bi-level optimization model; energy consumption; multimodal transportation systems.

## 1. BACKGROUND AND MOTIVATION

The current transportation system relies heavily on non-renewable fuel energy. It accounts for 71 percent of the nation's petroleum use and 30 percent of U.S. greenhouse gas emissions [12] [30]. These statistics suggest that reducing the energy consumption in the transportation sector can significantly enhance national energy security and help control greenhouse gas emissions. However, the current transportation system is central to the U.S. societal mobility and commerce and cannot be easily or quickly altered. Therefore, reducing the transportation system energy consumption without sacrificing mobility needs disproportionately is a key imperative, and motivates the current study.

The total energy consumption of the current transportation system is a function of the fuel efficiency of the transportation modes and the intensity of transportation mode usage [20]. Accordingly, a comprehensive approach is required to simultaneously: (1) avoid increased traffic activity and reduce current demand for transport; (2) shift demand to more efficient modes of transport such as public transit, walking, cycling and freight rail; and (3) improve the use of fuel efficient vehicles. The International Energy Agency [8] summarized these three principles in an Avoid-Shift-Improve (ASI) approach, which provides a holistic framework for strategic actions to foster sustainable transport systems. This study focuses on the commonly-addressed demand-side strategy of shifting traffic demand from low fuel efficiency modes to high fuel efficiency modes. Empirical data indicates that cars and light trucks used for personal travel alone account for the majority of fuel consumption in the transportation sector [12]. The fuel efficiency of transportation modes (per passenger per gallon) degrades in the order of rail, road, and air modes [27]. Hence, to reduce energy consumption in current transporting systems, the primary focus is on shifting the passenger traffic demand in cars, light-duty trucks, and air to high occupancy modes such as rail and public transit [28]. This raises the key question of how to foster such a traffic demand shift among different transport modes.

Strategic policies which influence transportation supplier actions as well as traffic mode choices represent a promising solution paradigm to realize the demand shift from low fuel efficiency modes to higher efficiency ones. Thereby, the three key players including the travelers (who form the traffic demand), transportation suppliers (who provide the traffic supply options), and policy-makers (who design and implement policy instruments), work independently in the short-term, but interactively in long-term to address energy consumption in the transportation sector. For example, transportation suppliers (who provide vehicles, fuel and traffic infrastructure, and

operate transportation modes and serve commercial freight and passenger) typically focus on profits. Their decisions and actions are significantly impacted by policy-makers through different instruments such as tax, subsidy, mandatory policies, etc. By contrast, travelers will choose intermodal/multimodal paths based on their preferences and level of service attributes of the modes (such as frequency, fare, travel time, and waiting time) provided by transportation suppliers. The mode choices of the travelers will eventually impact the operational decisions of transportation suppliers. Therefore, the interactions among the three players as well as their operational/behavior characteristics need to be considered so that a successful policy instrument can be implemented.

The conceptual perspectives discussed heretofore are well-recognized. The key gap to successfully implement a policy instrument for energy savings in the transportation sector is the need for a systematic and quantitative tool to predict the traffic demand shift, the energy consumption reduction, and the actions of transportation suppliers, so that the effects of energy policy can be holistically captured. However, as identified in the literature review in the next section, most existing studies only provide conceptual suggestions based on historical trends but cannot characterize these effects quantitatively. To address this gap, the proposed study proposes mathematical models to capture the energy consumption effects resulting from traffic demand shift and traffic supply operational actions, which are triggered by the implementation of certain policy with the goal to minimize energy consumption. While specific policy instruments are not explicitly included in the current model as decision variables, several key factors linking interactions between policy-makers and traffic suppliers, and policy-makers and travelers are incorporated such as profit threshold, gasoline price, etc. These linkages will enable us to investigate the impact of policy instruments on traffic suppliers and demands. Intercity multimodal transportation networks that include the private car, transit, rail, and air modes are considered in this context. Traveler preferences, transportation supplier operational constraints as well as the interactions among traffic demand and suppliers will be considered in the modeling process. The associated solutions can provide policy-makers in both the transportation and energy consumption sectors insights so that strategic policy instruments can be designed to realize traffic demand shifts and achieve system energy savings in the long-term.

The rest of the paper is organized as the follows. Section 2 reviews the past literature in this domain. Then, preliminaries including definitions, assumptions, and notations are provided in Section 3. The mathematical model and its solution methodology are described in Section 4 and 5 respectively. Next, Section 6 discusses numerical experiments and the associated insights. The paper concludes with some comments and insights related to the problem context in Section 7.

## **2. LITERATURE REVIEW**

Past studies in multimodal transportation system have addressed traffic demand [14], supply modeling, transportation policy making as well as their interactions [23][24]. However, holistic studies that integrate these aspects with broader system level objectives such as energy conservation are lacking. Thus, they typically address one of

the sub-problems rather than the broader perspective of this study. Garbade and Soss [5] analyze the interactions between traffic demands and suppliers. A dynamic model is developed to capture the relationships between demand, supply, cost and revenue in the market for mass transit services in New York City. Li and Wachs [13] propose several intermodal performance indicators in which service input, service output and service consumption are measured using total cost, revenue capacity, and unlinked passenger trips based on economic principles and evaluation objectives. Aifadopoulou et al. [1] explore the routing problem in multimodal transportation networks. A multi-objective optimum path algorithm, identifying feasible paths according to compatibility of various modes, intermodal stations, and users' preferences, is designed for passenger pre-trip planning. Hamdouch et al. [7] propose a toll pricing framework, and conduct a congestion pricing study for multimodal transportation systems. Todd [29] summarizes basic principles for multimodal transportation planning and evaluation, and states that transportation modeling techniques are being enhanced to consider a wider range of options (such as pricing incentive and multiple modes) and impacts (such as emissions and land use). Savage and Schupp [23] conducted elaborate studies on transit subsidies in Chicago. Savage [24] explored the dynamics of fare and frequency choice in urban transit. Savage [25] analyzed the cross elasticity between gasoline prices and transit use based on data from Chicago. These studies investigated the sub-problems of this study, but no systematic methods were proposed for transportation policy making to reduce energy consumption. Szeto et al. [26] developed a multi-objective bi-level optimization model to consider the social, economic, and environmental dimensions in road network design. Chen and Wang [2] studied the interaction between three concurrent policies: greenhouse gas (GHG) emissions trading, green pricing programs and renewable portfolio standards (RPS), which are implemented in the United States to reduce reliance on fossil fuel and GHG emissions. The above two studies are relevant to the proposed study, but have different objectives.

A few studies have addressed the energy consumption and emission issues jointly (such as [19]) in transportation systems since these two problems are usually linked together. Most existing studies rely on examining current policies and their performances, and then propose conceptual strategic policy recommendations. For example, Poudenx [21] conducts a brief survey on twelve major cities with various policies in place to curb private vehicle use and assesses their success in terms of energy consumption and greenhouse gas emissions. Rickwood et al. [22] examine the current state of research in the energy and greenhouse gas emissions attributable directly or indirectly to urban form. Kenworthy [10] reviews transport, urban form, energy use and CO<sub>2</sub> emission patterns in an international sample of 84 cities. Policy recommendations to reduce urban passenger transport energy use and CO<sub>2</sub> emissions are outlined in the aforementioned studies ([21][22][10]); however, no quantitative mechanisms are proposed to predict the consequences of a policy implementation. They all indicate that detailed research is needed to examine the relationships among urban form, traffic demand and energy use in multimodal transportation systems. Zumerchik et al. [32] propose a metric to measure energy consumption in multimodal transportation systems, but the interactions between energy consumption, traffic demand, and transportation

suppliers are not explicitly incorporated. Euritt et al. [4] explore strategies to reduce energy consumption and CO<sub>2</sub> emissions in Texas. Four alternative scenarios, reflecting different strategies, are conducted based on Long-Range Alternative Planning/Environmental Data Base (LEAP/EDB). Pedersen et al. [20] identify policy options to reduce energy use and greenhouse gas emissions from the U.S. transportation context, though only strategic aspects and not quantitative analyses are provided. Hence, neither [20] nor [4] perform systematic quantitative analyses. Knittel [12] examines the primary mechanisms through which reductions in U.S. oil consumption might take place, including increased fuel economy of existing vehicles, increased use of non-petroleum-based low-carbon fuels, alternatives to the internal combustion engine, and reduced vehicle-miles travelled. The effects of these mechanisms are compared to using a Pigouvian tax in energy consumption reduction. In summary, extensive policy discussions and other analyses have been addressed based on historical data, but they mostly focus on fuel economics rather than predict energy consumption resulting from traffic demand shift and transportation supplier operational actions, which are the key factors considered in the proposed study.

The state of the art indicates that though several studies in recent years have broadly analyzed energy consumption issues in the transportation sector, systematic and quantitative analyses are lacking for multimodal transportation systems. There are gaps in terms of the need for analytical models that can demonstrate how energy policy instruments, aiming to minimizing energy consumption in transportation system, will affect traffic demand and supply, which will further transfer into the corresponding energy consumption output in the transportation sector. Without knowing this interaction, the goal of energy policy instruments may not be well reached. The key contribution of the proposed study is to partly bridge this gap by developing quantitative tools, which address the issues relevant to the design of energy saving strategies (with the aim to minimize system energy consumption in the transportation sector) by integrating the interactions among transportation demand, supply and energy consumption into the proposal mathematical model.

### **3. PRELIMINARIES**

The proposed research studies energy consumption issues in an intercity transportation system incorporating interactions between transportation supply (mode service characteristics in terms of fare, waiting time, travel time, and frequency) and demand (mode choice decisions) under the goal of policy-makers to mitigate system energy consumption in the long term. To formulate the associated analytical model, this section introduces the abstracted Intermodal Network (IN) and the associated variables and parameters in this study.

#### **3.1 Intermodal network**

The intercity transportation modes considered are private auto, transit (including metro), rail and air. The passenger traffic demand is divided into business and nonbusiness trips (including other types of trips such as leisure, personal etc) ([9][11]) considering their different attitudes to the mode service characteristics. The intermodal

transportation network available between an origin and destination is abstracted as an Intermodal Network, in which the node set  $N$  corresponds to the cities or the mode transfer terminals, and the link set  $E$  represents the available connections through the various transportation modes between the terminals or cities. Here, the individual links in the proposed intermodal network are differentiated by the connectivity associated with the mode rather than the specific physical connections on the ground or the departure/arrival schedules, since the proposed study emphasizes mode choice and route selection in an aggregated manner. Correspondingly, the variables or parameters associated with each link in the intermodal network are representative of all possible scheduled service time slots in a day or all available physical links in a network. For example, an IN employs only one link with an expected travel time and expected monetary cost to represent various road-based paths by private auto between an origin and a destination. Similarly, an expected fare is used to represent the travel cost for a certain transportation mode though in reality fares may vary by departure/arrival times for scheduled service systems. Such an abstraction mechanism is a deliberate approach to enable integration and capture the interactions among the disparate high-level problem characteristics addressed earlier.

### 3.2 Variables and parameters

This section defines the decision variables and parameters associated with intercity multimodal transportation systems. First, the indices are introduced: (1)  $i$ : index of modes,  $i \in I \{1, 2, 3, 4\}$  where 1, 2, 3, and 4 represent private auto, transit, rail, and air mode, respectively; (2)  $l$ : index of link,  $l \in \{1, 2, \dots, L\}$  where  $L$  is the total number of links; (3)  $h$ : index of intermodal paths,  $h \in \{1, 2, \dots, H\}$ , where  $H$  is the total number of intermodal paths; and (4)  $\kappa$ : index of traveler class,  $\kappa \in \{1, 2\}$ , where 1 and 2 refer to business trip and nonbusiness trip, respectively;  $K = 2$  is the total number of traveler classes. Next, the variables and parameters associated with each link in the *IN* are provided from the supplier, demand, and supply-demand interaction perspectives.

#### *3.2.1 Parameters and variables for transport supply side*

From the transportation supply side, this study considers these parameters. Each transportation mode  $i$  has a fixed capacity  $p_{li}^0$ . It consumes  $\delta_{li}$  gallons of gasoline to carry the travelers on the mode across a link  $l$  (note that this study converts different energy types into equivalent gasoline consumption). In addition, each transportation mode  $i$  has current frequency  $r_{li}^0$  times per day, and travelers need to wait  $w_{li}^0$  units of time, and travel  $t_{li}^0$  units of time to cross link  $l$  with fare/cost  $c_{li}^0$ . Let  $p = \{p_{li}^0\}$ ,  $\delta = \{\delta_{li}^0\}$ ,  $c^0 = \{c_{li}^0\}$ ,  $r^0 = \{r_{li}^0\}$ ,  $w = \{w_{li}^0\}$ , and  $t = \{t_{li}^0\}$  represent their corresponding sets. The fare of private auto mode is calculated by using the product of gas price ( $c^g$ ), and the expected energy consumption on link (that is  $c_{li}^0 = c^g \delta_{li}$ ). The reasonable service frequency of mode  $i$  on link  $l$  is bound by the interval  $[b_{li}^0, u_{li}^0]$ . Similarly,  $[b_{li}^0, u_{li}^0]$  represents the lower and upper bound of rational fare for mode  $i$  on link  $l$ .

To capture the variations in service due to changes in traffic demand, four variables  $c_{li}$ ,  $r_{li}$ ,  $w_{li}$  and  $t_{li}$  are introduced to denote the respective variations associated with travel fare/cost, service frequency, waiting time, and travel time of mode  $i$  on link  $l$ .  $c = \{c_{li}\}$ ,

$r^0 = \{r_{li}\}$ ,  $w = \{w_{li}\}$ , and  $t = \{t_{li}\}$  are used to represent the corresponding sets. The overall network capacity is represented by the product of  $rp$ . The intermodal mode-link-path incidence matrix is defined as  $M = \{m_h\}_H$  with sub-matrix  $m_h = [m_{li}^h]$ , where  $m_{li}^h = 1$  if intermodal path  $h$  uses mode  $i$  on link  $l$ , otherwise  $m_{li}^h = 0$ . For example, matrix  $m_1$  for an intermodal path 1 is:

$$\begin{array}{c} 1 \quad 2 \quad 3 \quad 4 \\ \begin{array}{l} 1: o-1 \\ 2: 1-2 \\ 3: o-3 \\ 4: 3-4 \\ 5: 4-s \\ 6: 2-s \end{array} \left[ \begin{array}{cccc} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{array} \right], \end{array}$$

where the rows/columns represent the corresponding links/modes included in the path. Then, path 1 in the  $IN$  implies that a traveler starts from origin ( $o$ ) and takes transit system link ( $m_1^{12} = 1$ ) to the first terminal 1, transfers to the rail system and arrives at terminal 2 ( $m_1^{23} = 1$ ), and finally chooses the auto mode (for example, a taxi) ( $m_1^{61} = 1$ ) to reach the destination  $s$ . Using travel fare as an example, the fare for an individual intermodal path  $h$  can then be computed as  $C_h = \sum_{(i,l)} c_{li} m_{li}^h$ , where the defined rule of the matrix operation is that the element  $C_h$  in the array  $C = \{C_h\}_{h=1}^H$  is equal to the sum of the products of the elements  $c_{li}$  and  $m_{li}^h$  as  $i = 1, 2, \dots, I$  and  $l = 1, 2, \dots, L$ .

### 3.2.2 Parameters and variables for transport demand side

From the traffic demand side, this study considers these parameters. The intercity trips are grouped into two classes, business trips (B) and nonbusiness trips (NB). The corresponding traffic demand is denoted by  $D^\kappa$ ,  $\kappa = 1, 2$ . A linear utility function factoring travel time, waiting time, travel fare, and service frequency is used to quantify the satisfaction of an individual traveler in the context of choosing an intermodal path  $h$ . Accordingly,  $a_t^\kappa$ ,  $a_w^\kappa$ ,  $a_c^\kappa$ , and  $a_f^\kappa$  are the parameters to represent the weights of travel time, waiting time, travel fare, and service frequency for traffic demand of class  $\kappa$  in the utility function. The value of the weight may vary with factors such as types of trips, season, etc [9]. This study assumes a deterministic O-D demand ( $D = \sum_{\kappa=1}^2 D^\kappa$ ).

Variables on the transport demand side include the following.  $x_h^\kappa$  represents the traffic demand of class  $\kappa$  on path  $h$ .  $x = \{x_h = \sum_{\kappa=1}^K D_h^\kappa\}$  represents the corresponding path flow set. Accordingly,  $y_{li}$  is used to represent the traffic flow of mode  $i$  on link  $l$ , and  $y = \{y_{li}\}$  represents its set.

### 3.2.3 Parameters and variables for S-D interaction

To capture the supply-demand (S-D) interactions, this study considers that if the traffic demand for mode  $i$  (only for transit, rail, and air) on link  $l$  is greater than  $\varepsilon \times 100\%$  of the seat capacity, then traffic demand is sufficient and the binary variable  $z_{li} = 1$ ;



otherwise it is set to 0. Similarly, if the traffic demand is less than  $\varepsilon \times 100\%$  of the seat capacity, then traffic demand is insufficient and the binary variables  $s_{li} = 1$ , otherwise 0.  $\varepsilon$  and  $\varepsilon$  are given parameters. For a given link,  $z_{li}$  and  $s_{li}$  cannot be 1 at the same time but it is possible that both  $s_{li}$  and  $z_{li}$  are equal to zero, which means the traffic demand is neither clearly sufficient nor clearly insufficient. According to the state of S-D relationship, transportation suppliers (for transit, rail, and air modes) may adjust their travel fare and service frequency to sustain their profit requirements or service level. Accordingly, this study defines variables  $\alpha_{li}^{\uparrow}$  and  $\alpha_{li}^{\downarrow}$  to represent the incremental and decremental rate of travel fare for mode  $i$  on link  $l$ , respectively. Similarly,  $\beta_{li}^{\uparrow}$  and  $\beta_{li}^{\downarrow}$  are used to represent the incremental and decremental rate of service frequency for mode  $i$  on link  $l$ , respectively.

Service level adjustments will lead to traffic demand ridership changes. We introduce the relevant parameters to capture this interaction.  $\zeta_{li}$  and  $\eta_{li}$  are used to represent the increasing or decreasing elasticity of travel fare for mode on link  $i, l$ , respectively;  $\zeta$  and  $\eta$  represent their corresponding sets. Similarly,  $\theta_{li}$  and  $\vartheta_{li}$  are used to represent the increasing or decreasing elasticity of service frequency for mode  $i$  on  $l$  link, respectively;  $\theta$  and  $\vartheta$  represent their corresponding sets. From a supply perspective, the service adjustment will impact profits;  $\pi_{li}^r$  and  $\pi_{li}^f$  are introduced as thresholds for ridership change rate, resulting from frequency and fare adjustment respectively, that lead to acceptable profit. They partially reflect the impacts of policy instruments on traffic supply. For example, the thresholds ( $\pi_{li}^r$  and  $\pi_{li}^f$ ) of transit mode is usually low since policy-makers usually provide subsidy to transit so that it can sustain its normal operation with no profit. This study refers  $\pi_{li}^r$  and  $\pi_{li}^f$  as profit thresholds for articulation simplicity.

A list of all notations and variables are provided in Appendix A.

## 4. MATHEMATICAL MODEL

### 4.1 Interaction Analyses

The interactions among transportation demand, transportation supply and energy policies are first analyzed at the conceptual level. Individual travelers (i.e. traffic demand) choose their paths before departure<sup>1</sup> based on their budget limits and the service characteristics of the intermodal paths. Transportation suppliers (i.e. transportation modes) provide transportation services. Their operational decisions<sup>2</sup> are made mainly under the need to sustain their operational profitability requirements (such as for rail and air operated by profit-driven agents) or service levels (such as for public transit operated by non-profit-driven agents). The energy policies are made with an emphasis on mitigating energy consumption in the transportation network. These three aspects may not be strongly linked in the short-term in that traffic demand and supply strategies may likely not consider network energy consumption. Thereby, in the short-term, a specific energy policy may not cause shifts in individual traveler mode/route

<sup>1</sup> This study assumes that the pre-determined path will not change during a trip.

<sup>2</sup> Private auto does not consider operational profit in this study.

choices or directly influence the operations of transportation supply. However, consistent with systems perspectives in transportation, the three aspects may interact in the long-term through a feedback-loop process. Thereby, the status of energy consumption can serve as a feedback/input to improve previous system policy implementation on the transportation network, and change the multimodal transportation system as a long-term effect. Incorporating the aforementioned interactions, the mathematical model discussed hereafter predicts the minimum system energy consumption under implemented policy instruments given that the traffic demand is optimally distributed among the transportation modes consistent with the modal utilities of travelers, and the transportation suppliers take collaborative actions to foster the energy consumption objective under acceptable profits or service levels.

#### **4.2 Bi-level Optimization Model**

This section proposes a bi-level decision framework denoted as *MP*. The upper level model aims to minimize the system energy consumption (objective of policy-makers) subject to transportation suppliers' operational constraints related to profit, operational decisions on frequency and fare, and the traffic demand distribution to paths resulting from the lower level model, which seeks to maximize the intercity trip utilities of travelers computed using a utility function. The decision variables in the upper level are the frequency, fare and the associated operational decisions on links with given traffic demand distribution among traffic modes, which are decided by the lower level. On the one hand, the service levels of transport modes in the upper level will affect the traffic demand distribution in the lower level. On the other hand, the traffic demand distribution will change the supply-demand relationship and influence the service levels of transport modes in the upper level. The interactions between the multimodal transportation suppliers and intercity traffic demand are considered under the goal of minimizing energy consumption at the system level. An optimal solution provides a traffic demand distribution to paths that results in the minimum system energy consumption under the specific policy implementation, which promotes the coordination of operational decisions from transport suppliers.

Before describing the mathematical model, two important considerations incorporated in the modeling process are discussed. First, the proposed model incorporates the effects of policy instruments through pertinent parameters on the transportation suppliers' side such as travel fare, gas price and profit threshold rather than directly factoring policy instruments as decision variables in *MP*, due to the lack of well-defined formulations to capture the relationships between transportation mode services and policy instruments. Instead, the impacts of policy instruments on the network energy consumption, suppliers' service as well as the traffic demand distribution to paths, are captured indirectly. Namely, the evolution of a policy instrument will change the associated parameters and then lead to a trajectory that reflects optimal energy consumption solutions. Second, the proposed model considers the profit requirements of the transportation suppliers except private auto as operational decision constraints (constraints (8) and (12)) in the upper level model of *MP* (i.e. any operational decisions need to ensure a ridership change rate leading to acceptable

profit<sup>3</sup>) rather than introducing a sub-level optimization model which maximizes the profits of suppliers, with the following considerations. (i) The profit requirements of different transport suppliers can be rather different. For example, while profit-making represents the main goal of the private transport suppliers, it is not a requirement in some public transportation modes, such as public transit systems. By contrast, limiting the energy consumption or greenhouse emissions may be more appealing to policy-makers. Hence, some policy options such as subsidies are usually provided to those traffic modes so that they can operate without being overly concerned about profits. (ii) We lack accurate formulations to capture the complicated interactions between the profits and operational decisions of transport suppliers.

The mathematical model is as follows. To assist the understanding of the mathematical model, we also illustrate the structure of the model in Appendix B.

$$MP \quad \text{Min} \quad \sum_l \sum_i r_{li} \delta_{li} \quad (1)$$

$$\text{s.t} \quad \epsilon r_{li} p_{li} - y_{li} \geq - \sum_{\kappa=1}^K D^\kappa z_{li}, i \in \{2, 3, 4\}, l \in L \quad (2)$$

$$\epsilon r_{li} p_{li} - y_{li} \leq \sum_{\kappa=1}^K D^\kappa s_{li}, i \in \{2, 3, 4\}, l \in L \quad (3)$$

$$z_{li} + s_{li} \leq 1, i \in \{2, 3, 4\}, l \in L \quad (4)$$

$$c_{l1} = c_{l1}^0, l \in L \quad (5)$$

$$c_{li} = \left(1 + \alpha_{li}^\uparrow z_{li} - \alpha_{li}^\downarrow s_{li}\right) c_{li}^0, i \in \{2, 3, 4\}, l \in L \quad (6)$$

$$b_{li}^c \leq c_{li} \leq u_{li}^c, i \in I, l \in L \quad (7)$$

$$\zeta_{li} \alpha_{li}^\uparrow z_{li} + \eta_{li} \alpha_{li}^\downarrow s_{li} \geq (z_{li} + s_{li}) \pi_{li}^c, i \in \{2, 3, 4\}, l \in L \quad (8)$$

<sup>3</sup> Recall that for transport modes operated by profit-driven agents such as air and rail, their acceptable profit thresholds is relatively high; for transport modes operated by non-profit-driven agents such as transit, their thresholds is relatively very low. Private auto does not have this issue since operational profit is considered.

$$r_{l1} = y_{l1}, l \in L \quad (9)$$

$$r_{li} = \left(1 + \beta_i^\uparrow z_{li} - \beta_i^\downarrow s_{li}\right) r_{li}^0, i \in \{2, 3, 4\}, l \in L \quad (10)$$

$$b_{li}^r \leq r_{li} \leq u_{li}^r, i \in I, l \in L \quad (11)$$

$$\theta_{li} \beta_i^\uparrow z_{li} + \vartheta_{li} \beta_i^\downarrow s_{li} \geq (z_{li} + s_{li}) \pi_{li}^r, i \in \{2, 3, 4\}, l \in L \quad (12)$$

$$\alpha_{li}^\uparrow \geq 0, i \in I, l \in L \quad (13)$$

$$\alpha_{li}^\downarrow \geq 0, i \in I, l \in L \quad (14)$$

$$\beta_{li}^\uparrow \geq 0, i \in I, l \in L \quad (15)$$

$$\beta_{li}^\downarrow \geq 0, i \in I, l \in L \quad (16)$$

$$z_{li} \in \{0,1\} \text{ and } s_{li} \in \{0,1\}, l \in L, i \in I \quad (17)$$

$$y = \sum_{\kappa=1}^K \sum_{h=1}^H x_h^\kappa m_h \quad (18)$$

$$\rho_h^\kappa = a_c^\kappa \sum_l \sum_i c_{li} m_h^{li} + a_w^\kappa \sum_l \sum_i w_{li} m_h^{li} + a_t^\kappa \sum_l \sum_i t_{li} m_h^{li} + a_r^\kappa \sum_l \sum_i r_{li} m_h^{li}, h \in H, \kappa \in K$$

$$(19)$$

$$\max \sum_{h=1}^H \sum_{\kappa=1}^K \rho_h^\kappa x_h^\kappa \quad (20)$$

$$\text{s.t} \quad \sum_{h=1}^H \left( m_h^{li} \sum_{\kappa=1}^K x_h^\kappa \right) \leq r_{li} p_{li} \quad (21)$$

$$\sum_{h=1}^H \left( m_h^i \sum_{\kappa=1}^K x_h^\kappa \right) \leq r_{li} p_{li} \quad (22)$$

$$x_h^\kappa \geq 0, h \in H, \kappa \in K \quad (23)$$

$$t_{li} = t_{li}^0, i \in I, l \in L \quad (24)$$

$$w_{li} = w_{li}^0, i \in I, l \in L \quad (25)$$

In the formulation of *MP*, Equation (1) represents the objective function of the optimization model in the upper level model, which seeks to minimize the energy consumption over the multimodal transportation network subject to the constraints from Equation (2) to Equation (25), among which Equation (2) to Equation (19) represents the upper level constraints, and Equation (20) to Equation (25) represents the model in lower level.

The constraints from Equations (2) to (4) indicate whether the traffic demand of mode  $i$  on link  $l$  is sufficient or insufficient, according to its traffic capacity. Three possible cases are captured. Case 1,  $z_{li} = 1$ , and  $s_{li} = 0$ , indicates that traffic demand for mode  $i$  on link  $l$  is sufficient. Correspondingly, the transportation suppliers will either increase travel fare to moderate traffic demand or increase service frequency (please see Equation (6) and Equation (10), respectively) so that transportation suppliers can sustain current service level and profit. Case 2,  $z_{li} = 0$ , and  $s_{li} = 1$ , indicates that the traffic demand for mode  $i$  on link  $l$  is insufficient. Then, transportation suppliers will appropriately decrease travel fare or service frequency to sustain their profits (please refer to Equation (6) and Equation (10), respectively). Case 3,  $z_{li} = 0$ , and  $s_{li} = 0$ , indicates a state where the traffic demand is neither clearly sufficient nor insufficient. Thereby, transportation suppliers may apply a flexible strategy; the optimal strategy is determined by the bi-level optimization model itself. In addition, it is assumed that the operational decisions of the transportation suppliers of transit, rail and air modes need to sustain their profit requirements in all of the above three cases. The profit thresholds of different transportation modes are influenced by the policy instruments. For example, a public transit mode may have zero profit due to the subsidy provided by policy-makers. This leads to two more constraints: Equations (8) and (12). Correspondingly, Equations (7) and (11) provide the feasible ranges of the travel fare and service frequency.

Equation (5) indicates that the travel fare of private auto is not changed by traffic demand, but its “service frequency” can be easily increased to satisfy all traffic demand, as indicated by Equation (9). That is, the “service frequency” for private auto is simply its flow on that link. Equations (13) to (17) specify the feasible regions for the decision variables in the first level. Equation (18) maps the path flows to the link flows. Equation

(19) measures the utility of path  $h$  for the travelers in class  $\kappa$ , which also denotes the preference of those travelers for that path.

Equation (20) represents the objective function of the lower level model. It aims to maximize the utilities of all travelers in the intercity trips. Equation (21) and Equation (22) represent the traffic flow conservation constraint and the capacity constraint, respectively. Equation (23) indicates that the feasible path flow is nonnegative. Equation (24) and Equation (25) identify the travel time and waiting time, respectively, for each mode on an individual link.

As this study addresses a long-term planning and policy context, its focus is on determining the system optimal traffic network performance within the capacity of each transportation mode. Hence, the traffic congestion associated with the traffic demand assignment is not considered in the formulation. Correspondingly, static travel times (such as free flow travel times) for the private auto and transit, and static waiting times for transit, rail, and air modes, are employed. This leads to linear relationships in the lower level.

## 5. SOLUTION METHOD

The proposed bi-level optimization model is characterized by a mixed-integer nonlinear program at the upper level, and a linear program at the lower level. A bi-level optimization model is generally NP hard ([3][15]), precluding a polynomial time algorithm to find the global optimal solution of the proposed model unless P is equal to NP. A bi-level model with both continuous and integer variables (i.e. mixed integer bi-level model) is even more challenging. While Vicente et al. [31] proved that under certain conditions there is always an optimal solution for the bi-level problem with integer variables in both the upper and lower levels, solving it without enumerating all the cases is still very difficult. Methods for bi-level programming with integer variables mainly focus on linear problems [3][6][17]. Converting a bi-level model into a single level optimization model using KKT conditions, and embedding it into a branch-and-bound framework has been proposed to solve mixed integer bi-level models [6]. Along with the approach, this study develops a customized branch-and-bound solution methodology to explore the local optimal solutions based on the characteristics of the model. Next, the model transformation and the customized solution algorithm are described.

First, it is noticed that the bi-level optimization model includes binary variables (such as  $z$  and  $s$ ) at the upper level. Thus, this study relaxes the binary variables as continuous variables in  $[0, 1]$ . Then, the model becomes a continuous bi-level model with a nonlinear program at the upper level, and a linear program at the lower level.

Next, the continuous bi-level optimization model is further transformed into a mathematical program with complementarity constraints (*MPCC*) model by substituting the linear program at the lower level using its KKT conditions (which represent the necessary and sufficient optimality conditions). This *MPCC* model is a one-level nonlinear optimization model. The transformation procedure is as follows.

The Lagrangian function of the linear program at the lower level is written as

Equation (26), where  $\lambda$ ,  $\mu_{li}$ , and  $\gamma_h^\kappa$  are the Lagrangian coefficients corresponding to constraints in Equations (21), (22), and (23).

$$\begin{aligned} \mathcal{L}(x, \lambda, \mu, \gamma) = & \\ & \sum_{h=1}^H \sum_{\kappa=1}^K \rho_h^\kappa - \sum_{\kappa=1}^K \lambda^\kappa \left( \sum_{h=1}^H x_h^\kappa - D^\kappa \right) - \\ & \sum_{l=1}^L \sum_{i=1}^I \mu_{li} \left( \sum_{h=1}^H \left( m_h^{li} \sum_{\kappa=1}^K x_h^\kappa \right) - r_{li} p_{li} \right) + \sum_{h=1}^H \sum_{\kappa=1}^K \gamma_h^\kappa x_h^\kappa \end{aligned} \quad (26)$$

Through the Lagrangian function  $\mathcal{L}$ , the KKT conditions of the linear program (that is the linear programming complementarity slackness conditions) are derived and given in Equations (29) to (31). The bi-level optimization model *MP* is then re-written as a *MPCC* model by substituting the linear program at the lower level by its KKT conditions, subject to the integer variables in Equation (17) being relaxed to the continuous variables shown in Equations (27) and (28). The formulation of the *MPCC* model, where the unchanged constraints in the upper level of *MP* are denoted by *MP*<sup>1</sup>, is as follows.

$$\begin{aligned} \text{MPCC} & \quad \text{Min} \sum_l \sum_i r_{li} \delta_{li} \\ \text{s.t} & \quad \text{MP}^1 \end{aligned}$$

$$0 \leq z_{li} \leq 1, l \in L, i \in I \quad (27)$$

$$0 \leq s_{li} \leq 1, l \in L, i \in I \quad (28)$$

$$\rho_h^\kappa - \lambda^\kappa - \sum_{l=1}^L \sum_{i=1}^I \mu_{li} m_h^{li} + \gamma_h^\kappa = 0, h \in H, \kappa \in K \quad (29)$$

$$\sum_{h=1}^H x_h^\kappa = D^\kappa, \kappa \in K \quad (30)$$

$$0 \leq \gamma_h^\kappa \perp x_h^\kappa \geq 0, h \in H, \kappa \in K \quad (31)$$

$$0 \leq \mu_{li} \perp r_{li} p_{li} - \sum_{h=1}^H m_h^{li} \sum_{\kappa=1}^K x_h^\kappa \geq 0, i \in I, l \in L \quad (32)$$

Thus far, the bi-level model  $MP$  has been converted into an , with all integer variables being relaxed to continuous variables. Furthermore, to find a solution for the bi-level model  $MP$ , in which  $z$  and  $s$  are binary value we develop a customized branch-and-bound algorithm. Specifically, the algorithm starts from a solution of the  $MPCC$  model (some of the  $z_{li}$  and  $s_{li}$  variables are continuous values); then picks any pair of  $z_{li}$  and  $s_{li}$  (with continuous values in  $[0, 1]$ ) and assigns them to feasible binary values (such as  $z'_{li} = 1$ , and  $s'_{li} = 0$ ). Next, the new  $MPCC$  model is solved, and then different processes are executed on this branch based on the new solution: (i) If no feasible solution exists, this branch is pruned; (ii) If a new binary integer solution is obtained, this branch is fathomed. If the objective value of the new integer solution is better than the current best integer solution, this solution will substitute the current best candidate integer solution and its objective value becomes the new bound for the bi-level optimization model. Otherwise, the previous solution and bound are retained; or (iii) If a new non-integer solution is obtained, and it is worse than the best candidate integer solution, then this branch is pruned as the integer solution generated by branching more integer variables under this branch will be worse than the current integer solution. Otherwise, new integer variables are branched with continuous values under this branch until it is pruned or fathomed. The aforementioned branch-and-bound algorithm is repeated until all branches are visited.

The proposed algorithm is characterized by two features. (1) It operates on two integer variables (a pair of  $z_{li}$  and  $s_{li}$ ) by employing the features specified in constraint (4) so that we can reduce the number of branches that need to be examined in the branch-and-bound algorithm, and potentially reduce computational load (all the branches of  $z_{li} = 0$  and  $s_{li} = 0$  are removed). (2) After specifying the integer variable at each branch, we solve an  $MPCC$  model to local optimality by using the  $NLPEC$  solver in commercial software  $GAMS$ . Note that  $MPCC$  models are a class of  $MPEC$  (Mathematical programming with equilibrium constraints) models. General solvers for mixed integer nonlinear program are not able to solve it efficiently due to the complementary constraints. The  $NLPEC$  solver in  $GAMS$  is a well-accepted solver for  $MPEC$  models.

## 6. CASE STUDY

This section presents a case study to illustrate the applicability of the proposed methodology, and then discusses the associated insights.

### 6.1 Experiment setup

Intercity trips from Lafayette, Indiana to Washington, D.C. are used to illustrate the applicability of the proposed mathematical model. As shown in Fig. 1, the corresponding  $IN$  includes the nodes labeled by the cities Indianapolis, Pittsburgh and Washington, D.C., and the airports IND, BWI, IAD and DCA where travelers can switch transportation modes, to complete the trip. A case study with 150 intercity trips, four traffic modes, 15 intermodal links and 22 intermodal/multimodal paths is considered, which leads to a bi-level optimization model with 30 binary integer variables and 245 continuous variables. Each path is presented as a chain of links and a chain of modes. For example, path 1 is presented as the chain of links (1-4-8) with the



chain of modes (auto, air, transit).

Associated with the  $IN$  in Fig. 1, input data (travel time, travel fare, waiting time, etc.) were obtained online for each link through websites such as Greyhound, airports, Wikipedia, and the existing literature. Table 1a and Table 1b summarize the input data for this case study. Table 2 presents the utility function used in our experiments. The key factors (travel time, fare, service frequency, and waiting time) as well as their weights in the utility function are determined based on the traffic demand models given by Koppelman (1990).

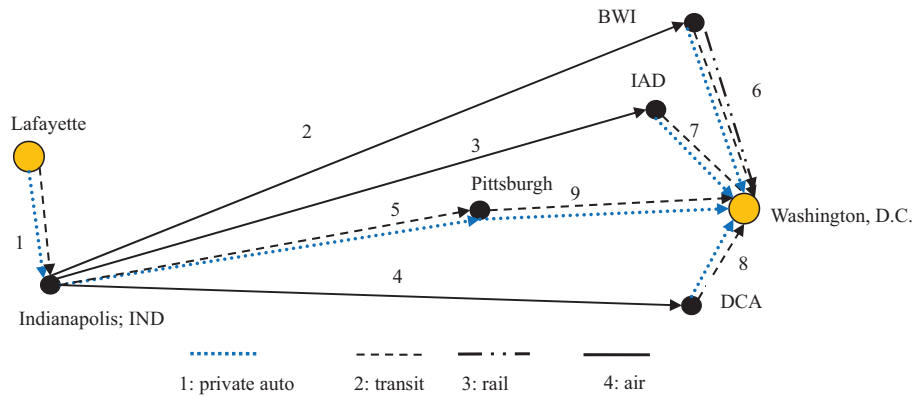


Figure 1. The intermodal network from Lafayette, Indiana to Washington, D.C.

**Table 1. Input data set in the case study**

Link	Mode	$p^0$	$\delta(\text{gallon})$	$c^0(\$)$	$t^0(\text{hour})$	$r^0$	$w^0(\text{hour})$
1	1	1	5	15	1	-	0
1	2	40	3	20	1.9	6	0.333
2	4	100	240	100	1.667	1	1.5
3	4	120	230	110	1.1	2	1.5
4	4	120	235	120	1.333	2	1.5
5	1	1	25	70	8.333	-	0
5	2	80	18	100	11.667	1	0.5
6	1	1	8	35	0.667	N	0
6	2	40	7	20	0.833	10	0.25
6	3	90	4	10	0.5	12	0.333
7	1	1	6	25	0.583	-	0
7	2	40	5	15	0.667	8	0.25
8	1	1	5	10	0.333	-	0
8	2	60	3	5	0.333	8	0.333
9	1	1	20	35	5	-	0
9	2	60	10	50	6.667	1	0.333

Link	Mode	$\theta&\vartheta$	$\zeta$	$\eta$	$b^r$	$u^r$	$b^c$	$u^c$
1	1	-	-	-	0.001	-	10	40
1	2	0.4	0.2	0.2	1	8	15	35
2	4	0.4	0.9	0.9	1	2	80	150
3	4	0.4	0.9	0.9	1	3	90	150
4	4	0.4	0.9	0.9	1	3	100	160
5	1	-	-	-	0	-	40	90
5	2	0.6	0.2	0.2	0	2	90	150
6	1	-	-	-	0	-	30	40
6	2	0.4	0.2	0.2	1	12	18	35
6	3	0.5	0.5	0.5	1	16	5	20
7	1	-	-	-	0	-	20	35
7	2	0.2	0.2	0.2	1	10	10	20
8	1	-	-	-	0	-	5	20
8	2	0.2	0.2	0.2	1	12	1	10
9	1	-	-	-	0	-	30	60
9	2	0.6	0.2	0.2	0	2	45	60

“-”: not applicable.

**Table 2. Coefficients in utility function**

Coefficients	Business trip $\kappa = 1$	Nonbusiness Trip $\kappa = 2$
$a_r^\kappa$	0.0006	0.0399
$a_c^\kappa$	-0.00256	-0.046
$a_t^\kappa$	-0.046	-0.00193
$a_w^\kappa$	-0.0157	-0.0066

The case study was solved in less than 10 minutes. The proposed approach can be applied for a large-scale problem, but may take a longer time to solve it. It is a branch-and-bound framework that can guarantee to stop in finite number of steps, and is embedded with the MPCC model, which can be efficiently solved using the NLPEC solver in the commercial software GAMS. The research issue in this study focuses on providing a decision framework for a long-term planning problem rather than real-time applications. Thus, computational load is not considered as a critical issue to be further emphasized here.

## 6.2. The Effects of Considering Energy in the Model

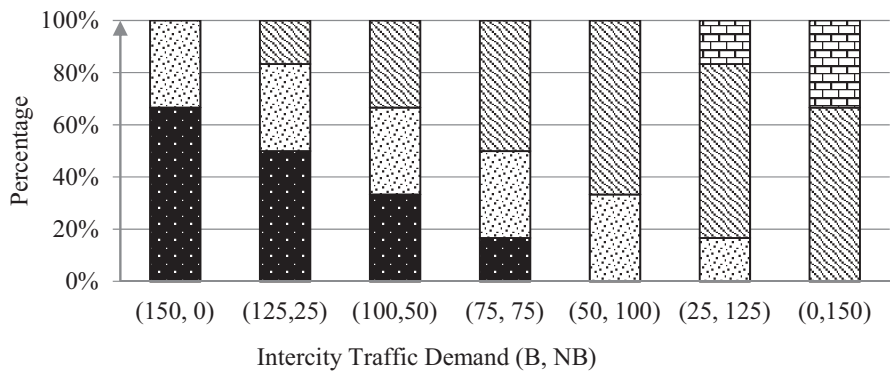
The effect of energy consumption consideration on the optimal traffic demand distribution among multimodal paths is analyzed under fixed traffic demand. Accordingly, two experimental scenarios are addressed. In the first scenario, without considering the system energy consumption, traffic demand is assigned so as to

maximize the utilities of travelers' trips. That is, the optimal traffic demand distribution is obtained by solving the lower level of the bi-level optimization model *MP*. Fig. 2(a) illustrates the associated results. In the second scenario, the traffic demand is distributed by considering the system energy consumption, the suppliers' operation, and the utility of travelers' trips. Accordingly, the system optimal solution is obtained by solving the bi-level optimization model *MP*. Fig. 2(b) shows the experiment results. All of the experiments are conducted under different combinations of business (B) and nonbusiness (NB) trips.

Fig. 2 indicates that when energy consumption is not considered, the solution to *MP* indicates that the traffic demand primarily chooses paths that include private auto for both business and non-business trips (see Fig. 2(a)). It is pertinent to note here that the intermodal path (auto, air, auto) is not chosen for business trips as its path utility is smaller than those of the paths (auto, air, rail) and (auto, air, transit) based on the case study data. As energy consumption becomes one of the considerations (that is, a policy instrument is implemented on the suppliers that triggers changes in service and profit levels), intermodal paths that include transit and rail are highly recommended for all traffic demand combinations (see Fig. 2(b)). Based on this traffic demand shift when energy consumption becomes a consideration (*EC\_opt*), the energy consumption is significantly reduced (see Fig. 2(c)). It also illustrates that when energy consumption is not considered (*EC\_org*), NB trips skew towards private auto usage (see Fig. 2(a)) leading to increased energy consumption. Along with the shift of the traffic demand to the intermodal path including transit or/and rail combined with air mode, the demand for rail and air approaches their capacities. With the current link capacities of rail and air unchanged, the bi-level optimization model *MP* suggests an increase in the travel fares of airline and rail links so that the suppliers can sustain service level as well as acceptable profits. These results indicate the required actions from transportation supplier side (see Fig. 2(d)). It can also imply collaboration between suppliers and policy-makers. For example, the government can provide subsidies to air and rail companies so that they can invest in additional capacity or operate under lower profit rates, thereby avoiding an increase in travel fares which reduces traffic demand. Similarly, most transit links are recommended to cut their current travel fares to attract more customers (see Fig. 2(d)), which indicates another role for policy-makers.

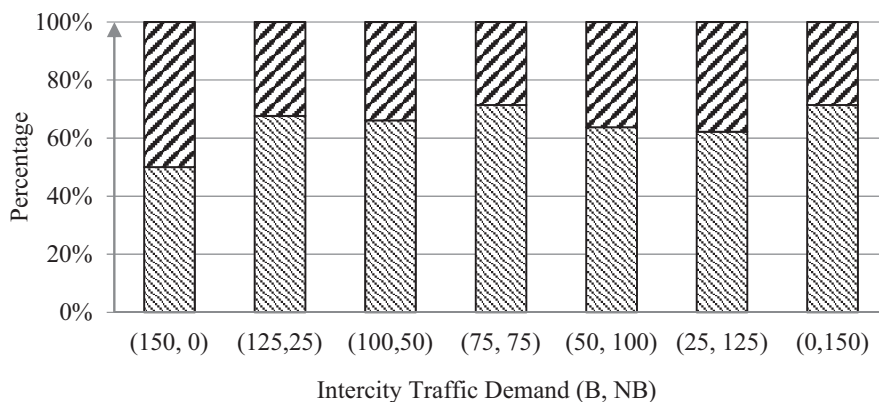
The above results first illustrate the capability of the proposed methodology to predict how the designed policy instruments related to energy consumption will translate to the corresponding traffic demand shift, transportation suppliers' actions as well as energy consumption output in the transportation sector. In addition, the systematic analyses suggest that shifting traffic demand from private auto to public transit or rail represents the key approach to mitigate system energy consumption, which is consistent with the commonly suggested solutions to this problem. Further, the results reinforce a well-known key deficiency related to current national energy conservation strategies. That is, most of the energy conservation strategies are focused on transportation suppliers (such as mandates for "fuel-efficient" vehicles), while the private auto travel mode is relatively untouched for multiple reasons. Thereby, many travelers use private auto instead of the energy-conserving public transportation

alternative. It points to the need to explore policy instruments (such as increasing gasoline tax, emission tax, etc.) through systematic quantitative analyses that capture the system-level interactions and emergent phenomena to develop robust strategies that are deployable and effective. The results also indicate that the intermodal trips that include the air mode are strongly recommended by the model in both scenarios, though current studies (Zumerchik et al., 2011) indicate that the air mode has relatively low energy efficiency in shipping passengers. This interesting finding implies that the energy efficiency of intermodal paths may perform differently compared to the energy efficiency of individual modes. Therefore, it may be more meaningful to consider using the energy efficiency characteristics of intermodal paths instead of those of individual transportation modes as the basis to formulate system policies to serve the traffic demand under acceptable service levels.



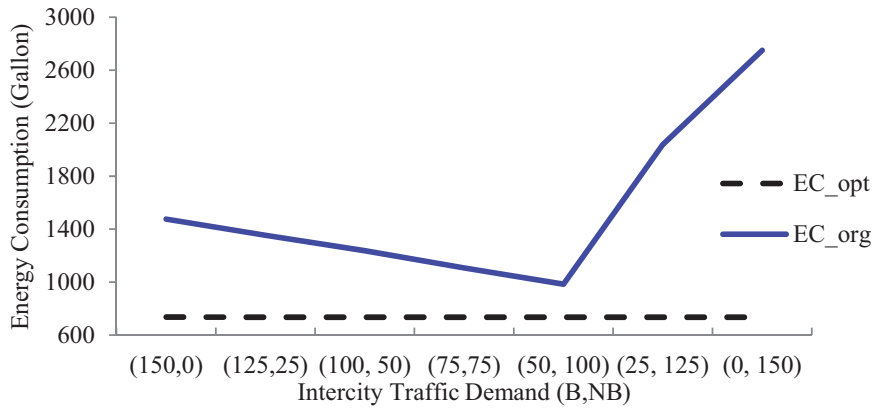
■ Auto, Air, Rail    ▨ Transit, Air, Rail    ▩ Auto, Air, Transit    ▧ Auto, Auto, Auto

(a) Traffic demand distribution only considering traveler preferences

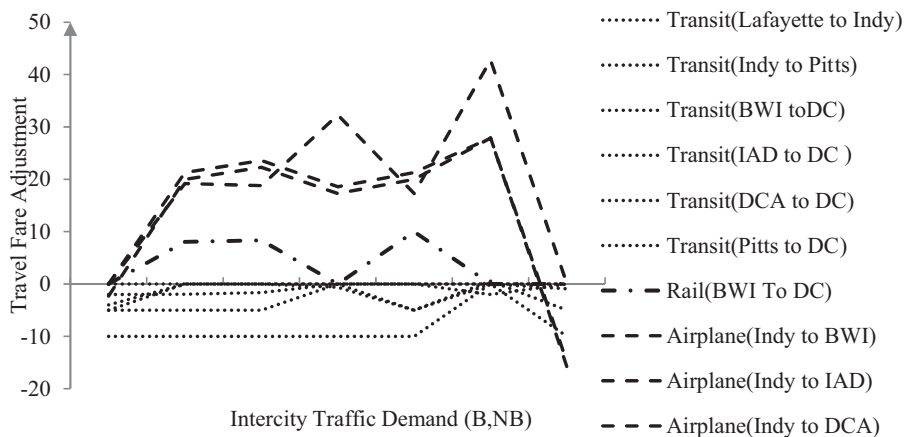


(b) Traffic demand distribution considering energy consumption

Figure 2. *continued over*



(c) Energy consumption under a traffic demand distribution with (EC\_opt) and without (EC\_org) considering energy consumption



(d) Travel fare adjustment for different links in the intermodal network

Figure 2. Effect of energy consideration (note that the x-axis label is identical to that of Figures 2 (a), (b) and (c))

### 6.3 Impact of Highway Travel Time on System Energy Consumption

The next set of experiments investigates the impact of highway travel time on the system traffic demand distribution under the goal of energy saving. They also demonstrate the capability of the proposed methodology to track the effect of traveler preferences, network structure, and supplier operational scheme on system energy consumption.

Three scenarios of highway travel time (representing different levels of the service)

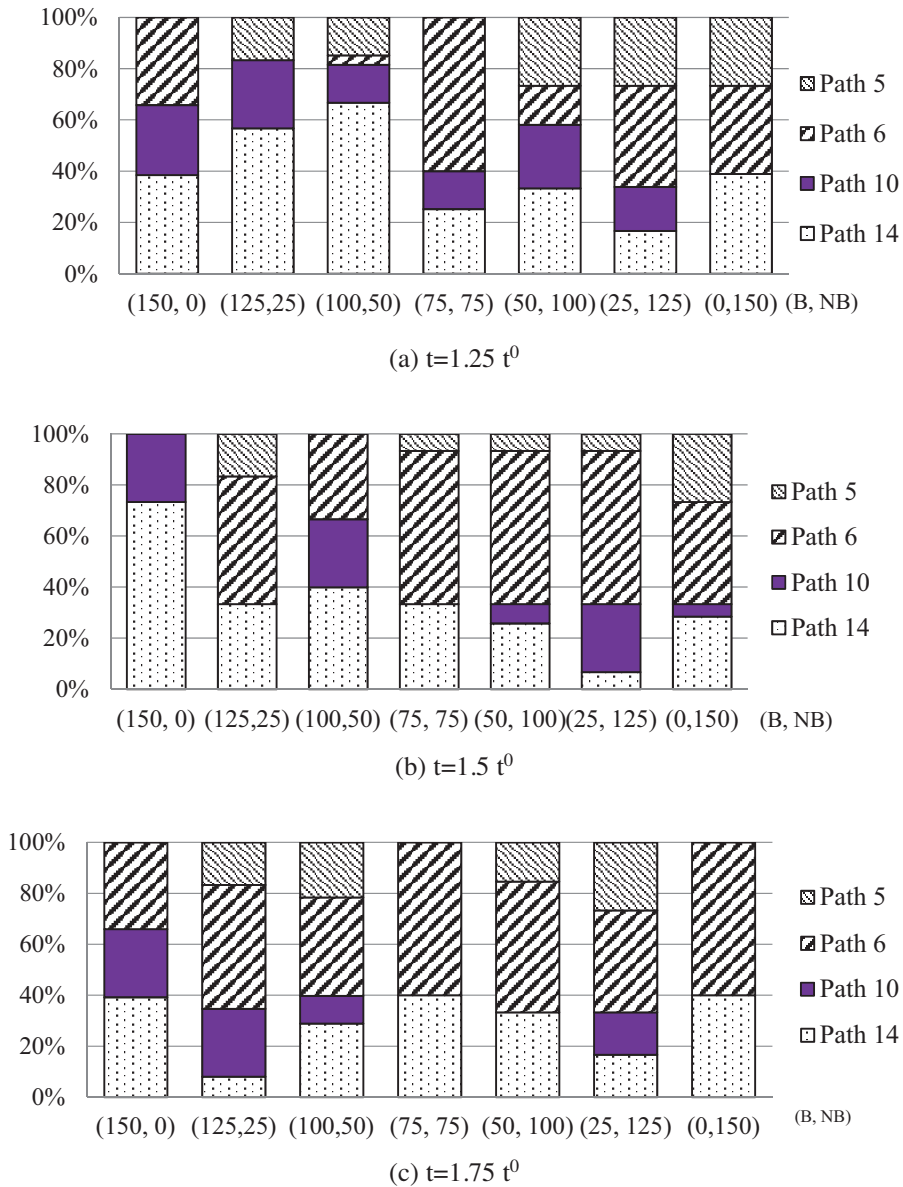
are considered; the highway travel time is increased by 1.25, 1.5, or 1.75 times its original value  $t^0$ . The associated optimal distributions of traffic demand to paths are summarized in Fig. 3, where the x-axis in each figure represents the traffic demand under different combinations of business and nonbusiness trips (B, NB), and the y-axis denotes the share of the corresponding intermodal travel option (path). Four intermodal paths cover all the traffic demand in each scenario: path 5 (node chain: 1-2-6; mode chain: transit, air, and transit), path 6 (node chain: 1-2-6; mode chain: transit, air, and rail), path 10 (node chain: 1-3-7; mode chain: transit, air, and transit), and path 14 (node chain: 1-4-8; transit, air, and transit). Typically, Paths 6 and 14 entail significant ridership, and Paths 5 and Path 10 have lesser ridership.

As the highway service becomes worse (from the scenario in Fig. 3(a) to the scenario Fig. 3(c)), the ridership of Path 14 decreases while that of Path 6 increases over different traffic demand compositions. It indicates that some traffic demand shifts from path 14 (transit, air, and transit) to Path 6 (transit, air, and rail) due to the low level of highway service. Also, when the service of highway is at a moderately congested level (when highway travel time is 1.25 or 1.5 times  $t^0$ ) and the business trip represents the main traffic demand, Path 14 has higher ridership than Path 6 (see Fig. 3(a) and Fig. 3(b)). However, when highway service becomes even worse (Fig. 3(c)) and nonbusiness trips represent the main traffic demand, Path 6 is more preferred. These two observations indicate that when the highway service becomes worse, policies to improve rail service can attract travelers to the intermodal path that includes the rail mode. It would potentially represent a good solution to satisfy the requirements related to both traffic demand mobility and system energy consumption.

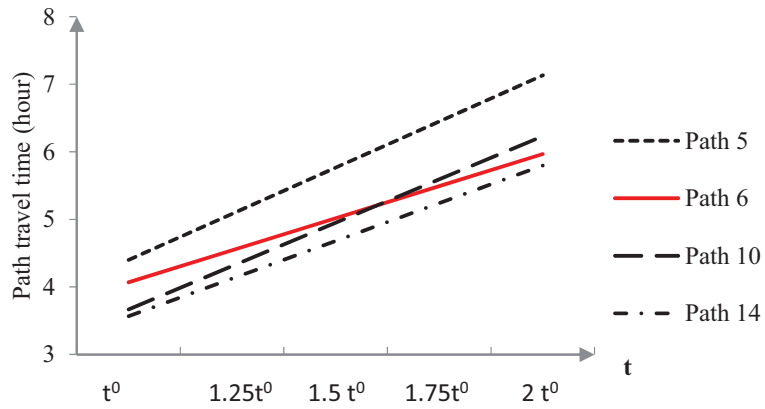
Fig. 4 compares the four intermodal paths in terms of travel time, travel fare, and energy consumption. While Paths 5, 10, and 14 have the same transportation mode chain (transit, air, and transit), their characteristics vary. Fig. 4(a) illustrates that Paths 14, 10, and 6 have similar travel times, and perform better than Path 5. Fig. 4(b) indicates that Path 6 requires a lower travel fare than Paths 5, 14, and 10 (the most expensive one). Thereby, Paths 5 and 10 have apparent disadvantages in travel time and travel fare, respectively. Therefore, to balance the benefits in terms of travel time and fare, travelers may prefer Path 6. Fig. 4(c) shows that Paths 10 and 14 are attractive from the energy savings perspective, with Path 10 having the least energy consumption. Hence, there are tradeoffs involved when all three factors are considered.

Neither Path 6 nor Path 10 can individually lead to the optimal solution of the proposed bi-level optimization model when the tradeoffs between traveler preferences (represented by trip utility) and system energy consumption are systematically considered in an integrated framework. Consequently, the optimal traffic demand distribution to intermodal paths resulting from the bi-level model assigns more traffic demand to Paths 6 and 14 rather than Paths 5 and 10, for all scenarios. Furthermore, since Path 6 has a travel fare advantage over Path 14 as the proportion of nonbusiness traffic demand increases, some traffic demand is shifted to Path 6 as non-business trips are more sensitive to travel fare (see the utility function in Table 2). Also, as the traffic on the highway becomes more congested, the advantage of Path 14 relative to travel time decreases; correspondingly, more traffic is assigned to Path 6.

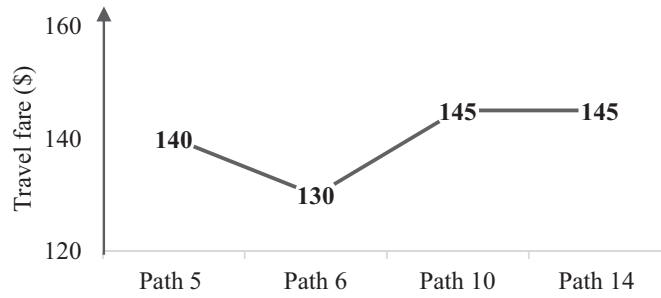
The detailed analyses indicate the difficulty of developing energy saving strategies for multimodal transportation networks. They also illustrate the capability of the proposed mathematical model to enable policy-makers to track the evolution of system energy consumption along with the variation of different factors such as traffic mode energy consumption efficiency, network structure, highway traffic conditions, travel fare, etc. The model can also aid policy-makers to identify interaction effects, enabling them to develop more robust strategies for energy conservation in the transportation sector.



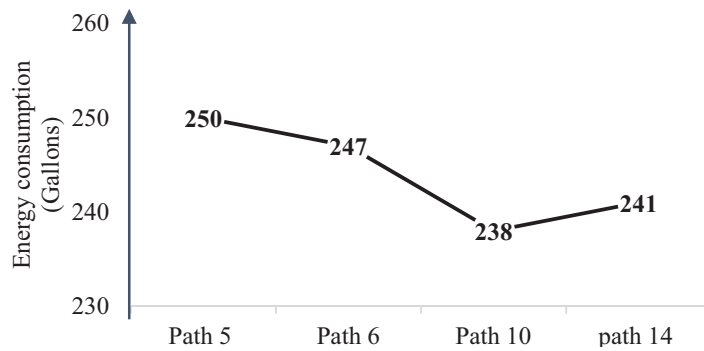
**Figure 3.** Traffic flow distribution among paths



(a) Travel Time



(b) Travel fare



(c) Energy consumption

Figure 4. Travel time, travel fare, and energy consumption of intermodal paths 5, 6, 10, and 14



## 7. CONCLUDING COMMENTS

This study proposes a quantitative and systematic methodology for policy-makers to reduce energy consumption in multimodal intercity transportation systems by incorporating the impacts of policy instruments indirectly in terms of changes in model parameters. A bi-level optimization model is proposed that considers suppliers' operational constraints and travelers' mobility requirements. Traveler preferences, transportation suppliers' operational constraints, as well as the interactions between travelers, suppliers and policy-makers, are incorporated in the modeling process. Multiple transportation modes including private auto, transit, rail, and air are considered, and traffic demand is differentiated into business and nonbusiness trips. The bi-level model is solved using a customized branch-and-bound algorithm with a *MPCC* model embedded at each branch.

Numerical experiments are conducted using a multimodal traffic network covering some intermodal routes from Lafayette, IN to Washington, D.C. The results reiterate that partly shifting traffic demand from private auto to transit and rail will significantly reduce energy consumption. The increment of travel fares in most transportation modes along with this shift indicates that the whole community needs to share the costs associated with the energy savings objective. In a practical implementation context, policy-makers can use subsidies to ensure that modes such as public transit entail low fares based on social welfare considerations. However, subsidies also are paid for by the community. The results also indicate that systematically considering traffic mode energy efficiency, traveler preferences, and network structure will lead to a better energy saving strategy than factoring only the energy efficiency of individual modes. As highway service becomes worse, policy instruments which shift more traffic demand to intermodal paths that include the rail mode can potentially satisfy the traffic demand needs and also mitigate system energy consumption.

More importantly, the experiments illustrate that the proposed methodology is able to provide quantitative analyses for system energy consumption and traffic demand distribution among transportation modes under specific policy instruments. It enables policy-makers in both the transportation and energy sectors to analyze the trajectories of system energy consumption and traffic demand shifts along with the evolution of the policy instruments or traffic infrastructure and supply (such as traffic mode services, traffic dynamics, and network structure changes). Thus, the proposed systematic and integrated analytical methodology bridges a key gap related to the ability to study the effects of policy instruments on the corresponding energy consumption output in the transportation sector. It also suggests the perspectives that focus on intermodal path characteristics rather than individual modes in isolation are more meaningful in developing energy-efficient policies.

The proposed methodology provides a platform to study other energy-related issues in multimodal transportation networks. Our near future work will apply the proposed model to a large scale network as more relative data are collected. Moreover, a potential extension is to vary the gas prices in the current mathematical model to explore how gas prices impact the system energy consumption in the transportation sector. Further, the proposed mathematical model can be enhanced to include policy instrument variables

so that the interactions between policy-makers and transportation suppliers can be explicitly captured in the mathematical model.

## ACKNOWLEDGMENTS

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## APPENDIX A: NOTATION LIST

For parameters with units, we specify them when input data are introduced in the case study.

### 1. Parameters

- 1)  $l$ : index of the physical link,  $l \in \{1, 2, \dots, L\}$ .
- 2)  $i$ : index of mode,  $i \in \{1, 2, \dots, I\}$ .
- 3)  $h$ : index of intermodal paths,  $h \in \{1, 2, \dots, H\}$ , where  $H$  is the total number of possible intermodal paths.
- 4)  $\varepsilon$ : parameter in  $(0, 1)$ , forms the threshold which identify sufficient traffic demand.
- 5)  $\epsilon$ : parameter in  $(0, 1)$  forms the threshold which identify insufficient traffic demand.
- 6)  $\delta_{li}$ : expected energy consumption of mode  $i$  on link  $l$  per trip;  $\delta = \{\delta_{li}\}$  represents the set
- 7)  $c_g$ : gas price.
- 8)  $p_{li}$ : expected seat capacity of mode  $i$  on link  $l$  per trip,  $p = [p_{li}]_{li}$  represents the set.
- 9)  $\zeta_{li}, \eta_{li}$ : increasing or decreasing elasticity of travel fare for mode  $i$  on link  $l$ ;  $\zeta = \{\zeta_{li}\}$ , and  $\eta = \{\eta_{li}\}$  represent the sets, respectively.
- 10)  $\theta_{li}, \vartheta_{li}$ : increasing or decreasing elasticity of service frequency for mode  $i$  on link  $l$ ;  $\theta = \{\theta_{li}\}$ , and  $\vartheta = \{\vartheta_{li}\}$  represent the sets, respectively.
- 11)  $\pi_{li}^r, \pi_{li}^c$ : ride rate change thresholds for the adjustment of service frequency and travel fare that lead to acceptable profit for mode  $i$  on link  $l$ .  $\pi^r = \{\pi_{li}^r\}$ , and  $\pi^c = \{\pi_{li}^c\}$  represent the set respectively.
- 12)  $[b_{li}^f, u_{li}^f]$  represent the lower and upper bounds of rational frequency for mode  $i$  on link  $l$ , respectively.
- 13)  $[b_{li}^c, u_{li}^c]$  represent the lower and upper bound of rational fare for mode  $i$  on link  $l$ , respectively.
- 14)  $M$ : mode choice matrix of all paths. in which sub-matrix  $m_h = [m_h^i]$  where  $m_h^i = 1$  if intermodal path  $h$  uses link  $l$  and also chose mode  $i$  on link  $l$ .
- 15)  $c_{li}^0$ : original travel fare of link  $l$  by mode  $i$ ;  $c^0 = \{c_{li}^0\}$  represents the set.
- 16)  $r_{li}^0$ : original frequency of link  $l$  by mode  $i$ ;  $r^0 = \{r_{li}^0\}$  represents the set.
- 17)  $t_{li}^0$ : original travel time of link  $l$  by mode  $i$ ;  $t^0 = \{t_{li}^0\}$  represents the set.
- 18)  $w_{li}^0$ : original waiting time of mode  $i$  on link  $l$ ;  $w^0 = \{w_{li}^0\}$  represents the set.
- 19)  $a^\kappa$ : the weight of different factors in the utility function for traveler class  $\kappa$ .

- 20)  $\rho_h^\kappa$ : the utility of intermodal path  $h$  for traveler class  $\kappa$   
 21)  $D$ : total traffic demand;  $\sum_{\kappa=1}^K D^\kappa = D$ .

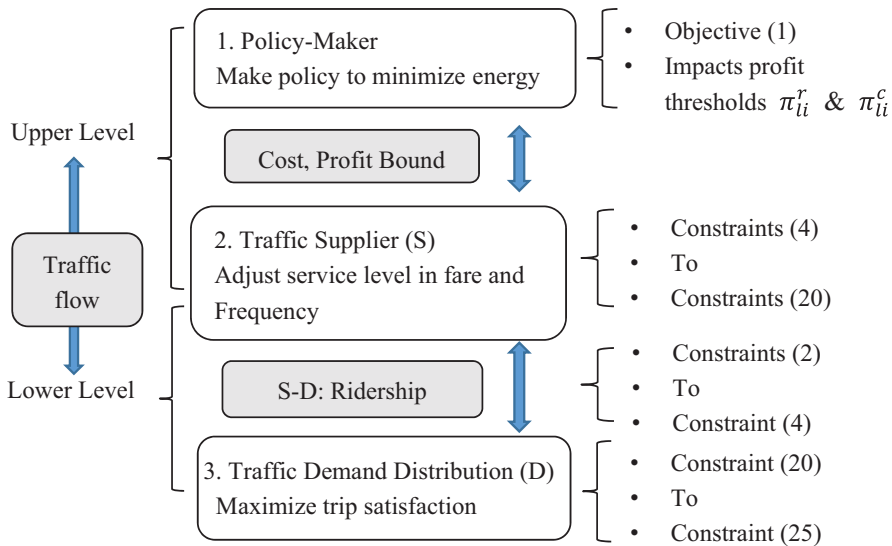
### 2. Variables

- 22)  $\alpha_i^\uparrow$ : travel fare incremental rate for mode  $i$  on link  $l$ ;  $\alpha^\uparrow = \{\alpha_i^\uparrow\}$  represents the set.  
 23)  $\alpha_i^\downarrow$ : travel fare decremental rate for mode  $i$  on link  $l$ ;  $\alpha^\downarrow = \{\alpha_i^\downarrow\}$  represents the set.  
 24)  $\beta_i^\uparrow$ : service frequency incremental rate of mode  $i$  on link  $l$ ;  $\beta^\uparrow = \{\beta_i^\uparrow\}$  represents the set.  
 25)  $\beta_i^\downarrow$ : service frequency decremental rate of mode  $i$  on link  $l$ ;  $\beta^\downarrow = \{\beta_i^\downarrow\}$  represents the set.  
 26)  $y_{li}$ : traffic demand of mode  $i$  on link  $l$ ;  $y = \{y_{li}\}$  represents the set.  
 27)  $x_h^\kappa$ : traffic demand of traveler class  $\kappa$  on intermodal path  $h$ .  
 28)  $c_{li}$ : expected travel fare of mode  $i$  on link  $l$ ;  $c = \{c_{li}\}$  represents the set.  
 29)  $r_{li}$ : expected service frequency of mode  $i$  on link  $l$ ;  $r = \{r_{li}\}$  represents the set.  
 30)  $t_{li}$ : expected travel time of mode  $i$  on link  $l$ ;  $t = \{t_{li}\}$  represents the set.  
 31)  $w_{li}$ : expected travel waiting time of mode  $i$  on link  $l$ ;  $w = \{w_{li}\}$  represents the set.

### 3. Binary Variables

- 32)  $z_{li} = 1$  indicates that traffic demand for mode  $i$  on link  $l$  is sufficient; otherwise it takes a value zero.  
 33)  $s_{li} = 1$  indicates that the traffic demand for mode  $i$  on link  $l$  is insufficient; otherwise it takes a value zero.

## APPENDIX B: STRUCTURE OF BI-LEVEL OPTIMIZATION MODEL



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