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Learning Drivers' Utility Functions in a Coordinated Freight Routing System Based on Drivers' Actions

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Learning Drivers' Utility Functions in a Coordinated Freight Routing System Based on Drivers' Actions

August 2024

A Research Report from the National Center for Sustainable Transportation

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16. Abstract

As urban areas grow and city populations expand, traffic congestion has become a significant problem, particularly in regions with substantial truck traffic. This study presents a coordinated freight routing system designed to optimize network utility and reduce congestion through personalized routing guidance and incentive mechanisms. The system customizes incentives and payments for individual drivers based on current traffic conditions and their specific routing preferences. Using a mixed logit model with a linear utility specification, the system captures drivers' route choice behaviors and decisions accurately. Participation is voluntary, ensuring most drivers receive a combined expected utility, including incentives, exceeding their anticipated utility under User Equilibrium (UE). This structure encourages drivers to follow suggested routes. Data collection on drivers' routing choices allows the system to update utility parameter estimates using a hierarchical Bayes estimator, ensuring routing suggestions remain relevant and effective. The system operates over defined intervals, where truck drivers submit their intended Origin-Destination (OD) pairs to a central coordinator. The coordinator assigns routes and payments, optimizing overall system costs and offering tailored incentives to maximize compliance. Experimental results on the Sioux Falls network validate the system's effectiveness, showing significant improvements in the objective function. This study highlights the potential of a coordinated routing system to enhance urban traffic efficiency by dynamically adjusting incentives based on drivers' choice data and driver behavior.

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Learning Drivers’ Utility Functions in a Coordinated Freight Routing System Based on Drivers’ Actions

A National Center for Sustainable Transportation Research Report

August 2024

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EXECUTIVE SUMMARY

As urban areas grow and city populations expand, traffic congestion has emerged as a significant problem, negatively impacting economic and environmental conditions, particularly in regions with substantial truck traffic. In this study, we present a coordinated freight routing system designed to optimize network utility and reduce congestion through personalized routing guidance and incentive mechanisms. This system customizes incentives and payments for individual drivers based on current traffic conditions and their specific routing preferences.

The proposed system uses a mixed logit model with a linear utility specification to capture drivers' route choice behaviors and decisions accurately. Participation in the system is voluntary, ensuring that most drivers receive a combined expected utility, including incentives, that exceeds their anticipated utility under User Equilibrium (UE), thus encouraging them to follow the suggested routes. The system continuously collects data on drivers' routing choices and updates utility parameter estimates based on recent decisions using a hierarchical Bayes estimator. This adaptation allows the system to dynamically refine its understanding of driver preferences, ensuring that routing suggestions remain relevant and effective.

To address the variation in drivers' route choice preferences, a logit mixture model is employed within the willingness-to-pay space. This model assumes that a truck driver evaluates a route based on several attributes, such as travel time, distance, speed limits, and the number of intersections. This model helps estimate drivers' preferences accurately, even without precise knowledge of individual utility parameters.

The system operates over defined intervals, where truck drivers submit their intended Origin-Destination (OD) pairs to a central coordinator. The coordinator assigns routes and corresponding payments, ensuring that drivers receive higher utility than they would under UE conditions. This process involves clustering drivers based on their utility parameters and optimizing route assignments and payments at the cluster level. By clustering drivers, the system can optimize overall system costs and offer tailored incentives to maximize compliance.

Experimental results on the Sioux Falls network validate the effectiveness of this approach. The system's performance is evaluated through various sensitivity analyses, and simulations show that the coordinated freight routing system can significantly improve the performance of the network.

1. Introduction

Traffic congestion has become a significant issue in modern urban environments, reducing residents' quality of life and causing considerable economic losses. In 2022, Americans spent an average of 51 hours annually in traffic jams, leading to an economic impact of $81 billion nationwide [1]. Beyond the financial costs, congestion worsens air pollution and negatively affects health, with vehicle emissions being a major pollutant [2],[3].

A major factor contributing to traffic congestion is the lack of coordination among road users. Without cooperation, individuals independently select routes to minimize their own travel costs [4]. This self-interested behavior, referred to in the literature as User Equilibrium (UE) [5], increases the overall system costs and reduces the efficiency of the transportation network.

Research in traffic management has focused on transitioning from UE to more efficient traffic distributions through various tolling methods. One prominent technique is congestion pricing, introduced in earlier studies [6], which proposes charging tolls on heavily congested roads to influence drivers' route choices and reduce traffic congestion. This approach has been explored in numerous studies, addressing aspects such as dynamic congestion pricing [7], the effects on diverse user value-of-time [8], and revenue management strategies from congestion tolls [9]. Besides congestion pricing, other innovative strategies to alleviate congestion include tradable credit schemes [10] and tradable travel permits [11], which allow drivers to trade travel rights within the network.

Recently, there has been a growing interest in using positive incentive policies to reduce traffic congestion, as these methods are often more favorable to both the public and policymakers [12]. Research has highlighted the effectiveness of such incentives in modifying commuter behavior, including changes in departure times and travel modes [13]-[17]. For example, a study conducted in Bangalore, India, aimed to ease congestion by encouraging commuters to travel during off-peak hours through monetary rewards [18]. This approach led to a significant shift in travel habits, resulting in lower average commute times. At Stanford University, the CAPRI program [19] aimed to mitigate peak-hour traffic by incentivizing alternative transportation methods like walking and biking. The program successfully promoted these alternatives and reduced commute times. Additionally, a study examined a lottery-based incentive system [20] to decrease congestion in urban transit by encouraging public transit use during less busy hours, demonstrating the potential of such strategies to manage traffic flow more effectively.

The advent of connected devices, such as mobile apps, and the rise of autonomous vehicles have underscored the potential for personalized incentives in transportation research [21]. These technologies enable a central coordinator to interact with travelers, monitor their choices, and tailor incentives based on individual preferences [22]. One example is Tripod [23], a real-time, smartphone-based system designed to influence travel decisions—such as mode of transport and departure time—through personalized information and incentives. Instead of just reducing travel time, Tripod aims to enhance overall energy efficiency. Another approach [24] combines behavioral modeling with optimization techniques to create customized travel incentives that encourage energy-efficient choices. Additionally, particle filters have been used in research to analyze individual responses and learn personal preferences [25], promoting sustainable travel behaviors. The Random Utility Maximization (RUM) framework [26][27] is commonly used to model user behavior and understand individual travel preferences. RUM posits that individuals choose the option with the highest utility among several alternatives. For more on discrete choice modeling and related estimations, we refer the interested reader to [28].

While earlier studies focus on influencing commuters' departure times and travel modes, our research is most closely related to the work found in [29], [30], [31], and [32]. These investigations study the use of personalized incentives to guide drivers' routing choices within transportation networks as a strategy to mitigate traffic congestion. For example, [29] introduced a distributed computational approach to address the large-scale optimization of offering personalized incentives to drivers, aiming to reduce overall travel time or other network costs. Studies [30], [31], and [32] involved a central coordinator managing route assignments and incentives for truck drivers to improve traffic flow through a budget-neutral method. Specifically, [31] incorporated user heterogeneity in value-of-time by using a multi-class model to ensure that each user class benefits more than they would under UE, thus achieving a Pareto improvement. Expanding on this, [32] included various factors beyond just value-of-time in the utility function, such as travel time and distance, and used a maximum likelihood estimation to determine the parameters of the proposed utility function.

This research introduces a coordinated routing system designed to optimize network efficiency and reduce congestion through personalized incentives and payments. Our system customizes incentives for alternative routes based on current traffic conditions and individual driver preferences. The objective is to ensure that the majority of drivers find their combined expected utility, including incentives, to be greater than their expected utility under UE, encouraging them to follow the suggested routes. The system collects data on drivers' route choices and continually updates utility estimates based on this information. To accurately model driver preferences, we use a logit mixture model and apply the Hierarchical Bayes method for estimating utility parameters. By incorporating driver feedback into a closed-loop system, our approach dynamically adjusts to actual driving behavior, providing a precise and adaptable representation of evolving preferences. Experimental results show that our coordinated routing system enhances network performance, with even more significant improvements when additional budget is available.

Our study concentrates on optimizing truck routes and evaluating a scenario where incentives are only offered to truck drivers for several key reasons. First, due to their larger size and slower speeds, trucks significantly disrupt general traffic flow. This slower movement leads to a disproportionately large impact on traffic congestion [33]. Second, since trucks are often confined to specific routes, implementing a coordinated routing system is more straightforward. Third, truck drivers regularly alter their routes based on traffic conditions for similar journeys, making them a suitable group for coordinated routing interventions. This framework can be easily modified to apply incentives to selected groups of drivers.

In this section, we differentiate our study from previous research, particularly focusing on the methodologies in [31] and [32]. Firstly, while [32] utilizes a cluster-based approach for utility learning and incentive distribution, our study emphasizes the customization of incentives at the individual level. By tailoring incentives based on each driver's unique utility parameters, we better match individual preferences, thereby enhancing compliance with assigned routes. Secondly, instead of relying on static survey data and a multinomial logit model with basic maximum likelihood estimation as in [32], our approach continuously updates utility parameters using actual driver behavior data. This ongoing adjustment, enabled by a logit mixture model, provides a more accurate and dynamic representation of driver preferences. Furthermore, [29] assumes that drivers choose routes based on fixed probabilities without considering the utility of different routes, which contrasts with our approach that integrates utility-based route choice. Finally, our method uses incentives as continuous variables, offering more flexibility and adaptability in their application. In contrast, [29] uses fixed discrete incentive values, which complicates practical implementation and can hinder algorithm performance.

This paper makes several key contributions: First, it introduces a personalized routing approach that dynamically adjusts to drivers' changing preferences by incorporating their historical routing decisions to reduce congestion. Second, it presents a new algorithm for distributing incentives, based on utility estimations derived from a mixed logit model. Third, our study evaluates the compliance rates of drivers and explores the consequences of non-compliance on overall system performance and revenue.

The paper is organized as follows: Section 2 covers the problem formulation. Section 3 describes the proposed methodology. Section 4 reports the simulation results. Finally, Section 5 concludes the paper.

2. Problem Formulation

Table 1 provides a summary of all key notations utilized in this paper. Scalar variables are represented without bold formatting. Vector variables are shown in bold lowercase letters. Matrices and higher-dimensional variables are denoted in bold uppercase letters. Sets are indicated using calligraphic font.

2.1 Transportation network

Let $G = (V, E)$ denote a transportation network, with V representing the set of nodes and E representing the set of road segments. This network accommodates both trucks and passenger vehicles. We assume there are W distinct Origin-Destination (OD) pairs for truck drivers. For each OD pair w, the available routes connecting the origin to the destination are represented by $\mathcal{R}^w = \{1,2, \dots, |\mathcal{R}^w|\}$.

Let N_{lP} be the number of passenger vehicles on road segment l. The travel time for road segment l is given by a known non-linear function $C_l(N_{lP}, N_{lT})$, where N_{lT} is the number of trucks on the same segment. The function C_l follows the Bureau of Public Roads (BPR) form:

$$C_l(N_{lP}, N_{lT}) = \gamma_a + \gamma_b \left(\frac{N_{lP} + 3N_{lT}}{\gamma_c}\right)^4$$

where $\gamma_a, \gamma_b, \gamma_c$ are constants. This equation is utilized in Sections 3.2 and 3.3 to model the travel times for truck routes.

2.2 Random utility model

We address the variation in drivers' route choice preferences by employing a logit mixture model [34] within the willingness-to-pay (WTP) space [35]. It is assumed that a truck driver evaluates a route based on L attributes, which may include factors such as travel time, distance, speed limits, and the number of intersections. Among these attributes, travel time is always considered a critical factor in route selection. It is further assumed that, for any route, only the travel time is influenced by the current traffic conditions, while other attributes remain constant. For driver n evaluating an alternative route j, let $\mathbf{x_{jn}} = \left(x_{jn}^1, x_{jn}^2, \dots, x_{jn}^L\right)$ denote the vector of L observable attributes for route j. In this vector, x_{jn}^1 specifically represents the travel time for driver n on route j.

Consider a scenario where a truck driver n chooses from among various alternative routes $j \in \mathcal{R}$. The utility of selecting route j for truck driver n, denoted as U_{jn}, is described as:

$$\begin{aligned} U_{jn} &= V_{jn} + p_{jn} + \beta_n \epsilon_{jn} \\ &= \mathbf{x_{jn}^{\mathit{T}}}\, \boldsymbol{\theta}_\mathbf{n} + p_{jn} + \beta_n \epsilon_{jn} \end{aligned}$$

Here, $V_{jn} = \mathbf{x_{jn}^{\mathit{T}}}\, \boldsymbol{\theta}_\mathbf{n}$ represents the observed utility and $\boldsymbol{\theta}_\mathbf{n} = (\theta_n^1, \theta_n^2, \dots, \theta_n^L)$ is the vector of parameters reflecting driver n 's preferences for the L observable attributes of a route. Given that x_{jn}^1 denotes the travel time for route j for driver n, θ_n^1 corresponds to the utility coefficient for travel time for driver n. We assume that $\boldsymbol{\theta}_\mathbf{n}$ follows a multivariate normal distribution: $\boldsymbol{\theta} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Omega})$, with $\boldsymbol{\mu}$ as the mean vector and $\boldsymbol{\Omega}$ as the covariance matrix. The error term ϵ_{jn} follows a Gumbel distribution, with $Var(\epsilon_{jn}) = \frac{\pi^2}{6}$. Additionally, β_n is the scale parameter associated with the error term for driver n.

The variable p_{jn} represents the payment that driver n receives for selecting route j. This model employs the Willingness-to-Pay (WTP) space notation as defined by [35], where the price coefficient is consistently set to 1. A positive p_{jn} indicates that the driver receives a payment from the system, whereas a negative p_{jn} means that the driver is charged by the system.

It is important to note that the coordinator cannot precisely know the exact value of $\boldsymbol{\theta_n}$. Instead, $\boldsymbol{\theta_n}$ can only be estimated based on the historical route choices made by driver n. Consequently, the estimate of $\boldsymbol{\theta_n}$ is denoted by $\widetilde{\boldsymbol{\theta_n}}$, and the estimate of β_n is denoted by $\widetilde{\beta_n}$. The method for estimating these parameters is detailed in Section 3.4.

2.3 Coordinated routing system

The coordinated routing system operates over defined intervals, which can range from several hours to a full day as set by the user. Before each interval begins, truck drivers scheduled to travel during that period must submit their intended OD pair w_n to the central coordinator. The entire group of truck drivers traveling in a particular period is represented as $\mathcal{D}$, while those planning to travel between a specific OD pair w are denoted as $\mathcal{D}^w$. For each planning period, the central coordinator works with a budget B, which is greater than or equal to zero.

Upon receiving the reported OD pairs from the truck drivers, the coordinator assigns each driver n a specific route $a_n \in \mathcal{R}^{w_n}$ along with the corresponding payment p_n, which could be either a charge or a reward. In addition to the assigned route a_n and the payment p_n, driver n is provided with details about the attributes of the assigned route a_n within the coordinated routing scheme, denoted as $\mathbf{x_{co,n}}$, where $x^1_{co,n}$ represents the estimated travel time.

Drivers can choose whether or not to participate in the coordinated routing system. A driver is incentivized to follow the assigned route if it offers higher utility compared to the UE scenario, where there is no central coordination and each driver independently selects routes to maximize personal utility. As a reference, drivers receive information about the UE route under the same traffic demand conditions, with the estimated route details at UE represented as $\mathbf{x_{ue,n}}$, where $x^1_{ue,n}$ is the estimated travel time. The process for determining the UE is explained in Section 3. With the assigned route a_n, payment p_n, and the estimated attributes $\mathbf{x_{co,n}}$ and $\mathbf{x_{ue,n}}$, drivers n is asked to decide whether to adhere to the assigned route. If they choose to follow a_n, they receive the payment p_n. If they decide against it, they are free to choose any other route from $\mathcal{R}^{w_n}$. The central coordinator tracks each driver's choice between the assigned route and an alternative route.

It is assumed that drivers lack precise knowledge of the travel times for their assigned routes when making their routing decisions. Instead, they rely only on the estimates provided by the system. We also assume that drivers do not incorporate their own judgments or external information about travel times into their decision-making process.

Table 1. Notations of frequently-used variables.

Variable	Meaning
W	The number of total OD pairs in the network
$\mathcal{R}^w$	The set of routes that connect OD pair w
L	The number of observed attributes of a route
K	The number of clusters for each OD in the clustering algorithm
$\mathcal{D}$	The set of all truck drivers in a period
$\mathcal{D}^w$	The set of truck drivers who intend to travel in OD pair w
B	The budget of the coordinator
$\boldsymbol{\theta}_{\mathbf{n}}$	The utility parameters of driver n
$\widetilde{\boldsymbol{\theta}_{\boldsymbol{n}}}$	The estimated utility parameters of driver n
w_n	The OD pair of driver n intends to travel
k_n^w	The cluster that driver n whose OD pair is w belongs to
a_n	The proposed route assignment of driver n
p_n	The proposed payment/incentive for driver n
$\mathbf{x}_{\mathbf{co,n}}$	The attributes of the assigned route of driver n
$\mathbf{x}_{\mathbf{ue,n}}$	The attributes of the route at UE of driver n
A, α	Cluster-based route assignments
$\boldsymbol{\Phi}, \phi$	Cluster-based payments/incentives
C_l	The travel time of road segment l
N_{lP}	The number of passenger vehicles that traverse road segment l
N_{lT}	The number of trucks that traverse road segment l
U_{rn}	The unobserved utility of alternative route r for truck driver n
V_{rn}	The observed utility of alternative route r for truck driver n
U	Total utility of the truck drivers
T	Total travel time of the passenger vehicles
O	The objective of the optimization problem

3. System Design

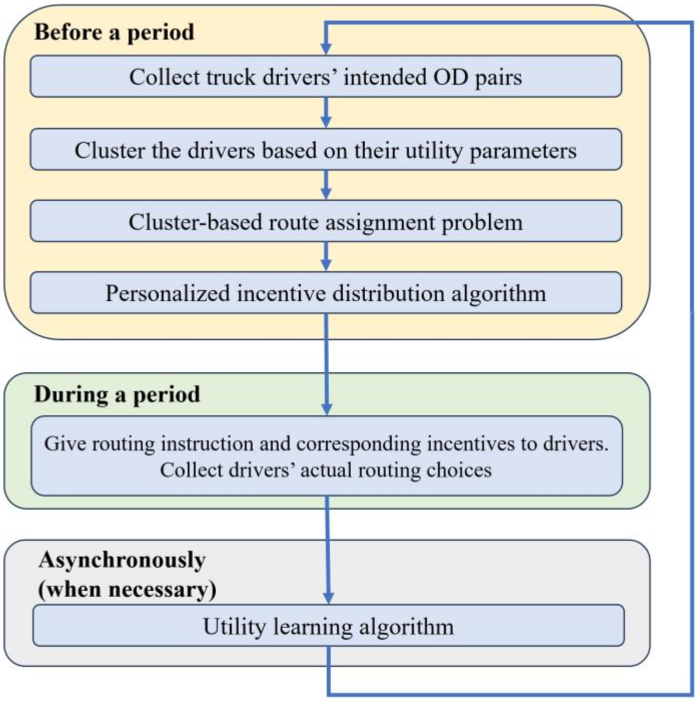

Figure 1. The structure of the proposed system.

The primary aim of the proposed system is to enhance the efficiency of the transportation network beyond the limitations of the UE by assigning personalized routes and offering payments to truck drivers. This improvement in efficiency is measured by combining the expected total travel time for passenger vehicles with the total utility derived by truck drivers, using a weighted sum. Participation in the system is voluntary, allowing truck drivers the choice to opt in or out based on their preferences.

In real-world situations, each driver has distinct routing preferences and utility parameters. The system estimates these parameters by analyzing the drivers' recent routing decisions. However, incorporating these individual utility parameters into an optimization model designed to minimize the overall cost of the transportation network greatly increases computational complexity, especially as the number of drivers grows.

To manage computational complexity, we first categorize all drivers into distinct clusters and then solve a cluster-specific route assignment problem to minimize system costs. Following this, we tailor payment schemes for each driver based on their assigned routes and estimated utility parameters, aiming to maximize participation through personalized incentives. By collecting drivers' actual route choices, we refine the utility function estimates for each driver based on their recent decisions. The overall system architecture is depicted in Figure 1.

3.1 Clustering the drivers based on their utility parameters

At the start of each period, the system collects information regarding the OD pair that each truck driver intends to traverse. The set of drivers planning to travel on a specific OD pair w is represented as $\mathcal{D}^w$. Additionally, the estimated utility parameter for each driver n, denoted as $\widetilde{\boldsymbol{\theta}_n}$, has been determined based on their past behavior. The K-means algorithm is utilized for clustering drivers, with the number of clusters K being an adjustable parameter. This clustering process, specific to each OD pair, is outlined in Algorithm 1.

Algorithm 1 Clustering Algorithm

Input: the group of drivers who intend to travel in OD pair $w = 1, 2, \ldots, W$, $\mathcal{D}^w$. The estimated utility parameter for driver $n \in \mathcal{D}$, $\tilde{\boldsymbol{\theta}}_{\boldsymbol{n}}$.

for OD pair $w = 1, 2, \ldots, W$ **do**
    Perform K-means algorithm to the set of truck drivers in $\mathcal{D}^w$ according to $\{\tilde{\boldsymbol{\theta}}_{\boldsymbol{n}}, \quad \forall n \in \mathcal{D}^w\}$
    for cluster $k^w = 1, 2, \ldots, K$ **do**
        $d_k^w \leftarrow$ the number of drivers in cluster k^w in OD pair w.
        $\bar{\boldsymbol{\theta}}_{\boldsymbol{k}}^{\boldsymbol{w}} \leftarrow$ the centroid of cluster k in OD pair w.
    end for
    for driver $n \in \mathcal{D}^w$ **do**
        $k_n^w \leftarrow$ the cluster that driver n belongs to.
    end for
end for

3.2 Cluster-based route assignment problem with system optimality consideration

With the centroid utility parameters identified for each cluster and the corresponding number of drivers, we design a cluster-based route assignment method aimed at optimizing the overall system cost.

For each cluster k^w within OD pair w, the method determines how to allocate drivers in the cluster to routes $r \in \mathcal{R}^w$ and calculates the corresponding payments for these drivers. Let $\boldsymbol{\alpha}_{\mathbf{k}}^{\mathbf{w}} = \left(\alpha_k^{w,1}, \ldots, \alpha_k^{w,|\mathcal{R}^w|}\right)$ represent the allocation for cluster k^w of OD pair w, where $\alpha_k^{w,r}$ indicates the proportion of drivers in cluster k^w of OD pair w assigned to route r. The overall allocation for all clusters is denoted by $\mathbf{A} = \{\alpha_k^{w,r}, w = 1, \ldots, W, k = 1, \ldots, K, r \in \mathcal{R}^w\}$. During this step, payments for each route are also calculated at the cluster level. Let $\boldsymbol{\phi}_{\mathbf{k}}^{\mathbf{w}} = \left(\phi_k^{w,1}, \ldots, \phi_k^{w,|\mathcal{R}^w|}\right)$ represent the payments for cluster k^w of OD pair w, where $\phi_k^{w,r}$ is the payment for a driver in cluster k^w of OD pair w if assigned to route r. The payments for all clusters are denoted by $\boldsymbol{\Phi} = \{\phi_k^{w,r}, w = 1, \ldots, W, k = 1, \ldots K, r \in \mathcal{R}^w\}$.

Let $\mathbf{x_{rw}} = (x_{rw}^1, x_{rw}^2, \dots, x_{rw}^L)$ represent the vector of attributes for route r within OD pair w. According to the established notation, x_{rw}^1 is defined as the travel time for route $r \in \mathcal{R}^w$. This variable, x_{rw}^1, is modeled as a function of the allocation matrix $\mathbf{A}$ using the BPR function, since $\mathbf{A}$ determines the number of trucks on each network link. Besides travel time, route $r \in \mathcal{R}^w$ has other attributes $x_{rw}^2, \dots, x_{rw}^L$ that are independent of traffic volume and are assumed to be known beforehand. Thus, we express $\mathbf{x_{rw}}$ as a function of the allocation $\mathbf{A}$, denoted as $\mathbf{x_{rw}}(\mathbf{A})$.

Our objective is to minimize the overall cost within the transportation network. This cost is calculated as a weighted sum of the total travel time for passenger vehicles and the negative value of the total utility derived by truck drivers, with the inversion intended to maximize the utility for truck drivers. In the context of the cluster-based optimization problem, the total utility for truck drivers is defined as follows:

$$U(\mathbf{A}) = \sum_{w=1}^{W} \sum_{k=1}^{K} \sum_{r=1}^{R} \alpha_k^{w,r} \left(\mathbf{x_{rw}}(\mathbf{A})^T \, \bar{\boldsymbol{\theta}}_{\mathbf{k}}^{\mathbf{w}} \right)$$

The total travel time of passenger vehicles in the network is given by:

$$T(\mathbf{A}) = \sum_{l \in E} N_{lP} \, C_l\big(N_{lP}, N_{lT}(\mathbf{A})\big)$$

The total utility of truck drivers and the total travel time of passenger vehicles both depend on the allocation $\mathbf{A}$. The objective function can therefore be expressed as follows:

$$O(\mathbf{A}) = \lambda T(\mathbf{A}) - (1 - \lambda) U(\mathbf{A})$$

where $\lambda \in [0,1]$ is a weighting factor.

The optimization problem is formulated as follows:

$$\begin{aligned}
\underset{\mathbf{A},\boldsymbol{\Phi}}{minimize} \quad & O(\mathbf{A}) \\
s.t \quad & S_k^{w,r} \geq Q_k^w \qquad \forall w, k, r \in \mathcal{R}^w \\
& \sum_{w}^{W} \sum_{k}^{K} \sum_{r}^{R} d_k^w \, \alpha_k^{w,r} \phi_k^{w,r} \leq B \\
& \sum_{r}^{R} \alpha_k^{w,r} = 1 \qquad \forall w, k \\
& \alpha_k^{w,r} \geq 0 \qquad \forall w, k, r \in \mathcal{R}^w
\end{aligned}$$

where $S_k^{w,r}$ represents the expected utility of cluster k^w assigned to route r, given by:

$$S_k^{w,r} = \mathbf{x_{rw}}(\mathbf{A})^T \, \bar{\boldsymbol{\theta}}_{\mathbf{k}}^{\mathbf{w}} + \phi_k^{w,r}$$

Q_k^w denotes the expected utility for cluster k^w within OD pair w in a UE scenario. The detailed derivation of Q_k^w is provided in the Appendix.

The first constraint ensures that the expected utility from the assigned routes within each cluster meets or exceeds the expected utility in the UE scenario, which is key to motivating drivers to follow the assigned routes by ensuring they benefit from doing so. The second constraint ensures the total financial transactions—both disbursements and receipts—by the coordinator stay within the allocated budget, thereby ensuring the system's financial sustainability. The third constraint requires that the allocation variables for any given route sum to 1, while the fourth constraint mandates that these allocation variables fall within the range [0, 1]. The feasibility of the proposed optimization problem is assured, as the allocation aligned with the UE solution, along with $\phi_k^{w,r} = 0$, satisfies all the imposed constraints.

3.3 Personalized incentive distribution

In Section 3.2, we employ a cluster-based methodology to determine incentives, ensuring that a representative driver at the centroid of each cluster is motivated to participate in the coordinated routing scheme. However, this approach does not guarantee that every individual driver will be equally motivated, as their personal utility parameters may differ from those of the cluster centroid. Therefore, the first two constraints in the above optimization problem may not be applicable at the individual driver level due to these variations in utility parameters.

To address individual differences among drivers, this subsection focuses on their unique decision-making processes. We propose a heuristic for distributing incentives that assigns personalized payments to each driver. The purpose of this heuristic is to maximize participation in the assigned routes while staying within the budget constraints. Our aim is to make the incentives attractive enough to persuade the majority of drivers to comply with their assigned routes, accordingly enhancing the overall efficiency and effectiveness of our system.

During each period, the system assigns each driver n a specific route a_n from the set of available routes $\mathcal{R}^{w_n}$ corresponding to their OD pair w_n, along with a designated payment p_n, which can be either a disbursement or a charge. The assignment of a_n is carried out through a specific procedure: Within each cluster k^w of OD pair w, we examine all routes $r \in \mathcal{R}^w$. A proportion $\alpha_k^{w,r}$ of drivers is randomly selected and assigned to route r, where $\alpha_k^{w,r}$ represents the optimal solution obtained from Section 3.2. The method for calculating personalized incentives p_n is detailed later in this subsection.

In addition to receiving their assigned route a_n and payment p_n, driver n is also provided with the attributes of route a_n within the coordinated routing scheme, denoted as $\mathbf{x_{co,n}}$. The travel time, $x_{co,n}^1$, is derived from the allocation $\mathbf{A}^*$, which is the optimal solution to the optimization problem specified in Section 3.2. For comparison, and as a benchmark against the scenario without a coordinated routing system, drivers are also given estimated route information under user equilibrium, represented by $\mathbf{x_{ue,n}}$. This UE information is obtained through an individual-level simulation model [36], as detailed in Algorithm 2.

Algorithm 2 Simulated User Equilibrium

1: Initialize the number of passenger vehicles on each link.
2: **while** the convergence criteria are not met **do**
3: Update the travel times for all links as per (1).
4: For each OD pair w, randomly select a subset of drivers $\mathcal{D}_{\eta}^{w}$ from $\mathcal{D}^{w}$ by choosing a fraction η.
5: Simulate route selection for drivers in $\mathcal{D}_{\eta}^{w}$. For each driver $n \in \mathcal{D}_{\eta}^{w}$, determine the utility of each available route $r \in \mathcal{R}^{w}$, and assign the route with the highest utility to driver n. The chosen route for driver n is given by: Driver n's route at the UE $\leftarrow \underset{r \in \mathcal{R}^{w}}{\operatorname{argmax}}\{\mathbf{x}_{\mathbf{rw}}^{\mathbf{T}}\ \tilde{\boldsymbol{\theta}}_{\boldsymbol{n}}\}$, where $\mathbf{x}_{\mathbf{rw}}$ is the attributes of route $r \in \mathcal{R}^{w}$ in this simulation.
6: **end while**

The convergence criterion requires that over the duration of M iterations, the difference between the maximum and minimum travel times for each truck route must not exceed a predetermined percentage threshold τ. The parameters η, M, and τ are set prior to the simulation.

Next, we evaluate whether the assigned route provides driver n with improved utility. When driver n follows the assigned route $\mathbf{x_{co,n}}$, the utility is given by:

$$U_{co,n} = \mathbf{x}_{\mathbf{co,n}}^{T}\ \boldsymbol{\theta}_{\mathbf{n}} + p_n + \beta_n \epsilon_{co,n}.$$

In the absence of the coordinated routing system, the scenario most familiar to the driver is represented by the UE, where the utility is given by:

$$U_{ue,n} = \mathbf{x}_{\mathbf{ue,n}}^{T}\ \boldsymbol{\theta}_{\mathbf{n}} + \beta_n \epsilon_{ue,n}.$$

Since the actual utility parameter $\boldsymbol{\theta}_{\mathbf{n}}$ is not precisely known to the system, we use an estimated utility parameter $\widetilde{\boldsymbol{\theta}_{\boldsymbol{n}}}$ to calculate driver n 's estimated utility for both the assigned route under the coordinated routing scenario and the route at the UE. We define the estimated utility of the assigned route as $\widetilde{U}_{co,n} = \mathbf{x}_{\mathbf{co,n}}^{T}\ \widetilde{\boldsymbol{\theta}_{\boldsymbol{n}}} + p_n$ and the estimated utility at the UE as $\widetilde{U}_{ue,n} = \mathbf{x}_{\mathbf{ue,n}}^{T}\ \widetilde{\boldsymbol{\theta}_{\boldsymbol{n}}}$.

We introduce a greedy heuristic incentive distribution algorithm for determining p_n, detailed in Algorithm 3. The main objective of this algorithm is to maximize the number of drivers for whom the estimated utility of their assigned route in the coordinated routing system surpasses that of the UE scenario by at least ξ, expressed as $\widetilde{U}_{co,n} \geq \widetilde{U}_{ue,n} + \xi$. This goal is pursued while keeping the total budget within its limit. The parameter ξ acts as a margin of error to account for the randomness in ϵ and estimation inaccuracies in $\widetilde{\boldsymbol{\theta}_{\boldsymbol{n}}}$.

Algorithm 3 Greedy Incentive Distribution Heuristics

Input: Estimated utility parameter for each driver $n \in \mathcal{D}$, denoted $\tilde{\boldsymbol{\theta}}_{\boldsymbol{n}}$. System assigned route attributes for each driver $n \in \mathcal{D}$, denoted $\mathbf{x_{co,n}}$. The UE route attributes for each driver $n \in \mathcal{D}$, denoted $\mathbf{x_{ue,n}}$.

for each driver $n \in \mathcal{D}$ **do**.
    Calculate utility difference:
        $\sigma_n := \mathbf{x}_{\mathbf{co,n}}^{\mathbf{T}} \ \tilde{\boldsymbol{\theta}}_{\boldsymbol{n}} - \mathbf{x}_{\mathbf{ue,n}}^{\mathbf{T}} \ \tilde{\boldsymbol{\theta}}_{\boldsymbol{n}} - \xi$.
    Initialize payment for driver n: $p_n = 0$.
end for
Initialize funding pool: $P = B$, where B is the budget of the coordinator.
Sort drivers in $\mathcal{D}$ by σ_n in descending order.
for each driver $n \in \mathcal{D}$ with $\sigma_n \geq 0$ **do**
    Set $p_n = -\sigma_n$.
    Update funding pool: $P = P + \sigma_n$.
end for
for each driver $n \in \mathcal{D}$ with $\sigma_n < 0$ and $P \geq 0$ **do**
    Set $p_n = -\sigma_n$.
    Update funding pool: $P = P + \sigma_n$.
end for

Output: Personalized payments p_n for each driver $n \in \mathcal{D}$.

The algorithm begins by targeting drivers who would achieve a substantially higher net profit from following the assigned route compared to the UE route. These drivers are charged, and the collected funds are added to a funding pool. Next, the algorithm distributes positive incentives to drivers who would incur a negative net profit from their assigned route compared to the UE route, prioritizing them based on their net profit in descending order.

3.4 Utility learning algorithm

To model drivers' routing choices, we use the logit mixture model outlined in Section 2.2. This model includes hierarchical parameters with two levels of estimation: the individual-level mean $\boldsymbol{\theta}_{\mathbf{n}}$, the population-level mean $\boldsymbol{\mu}$, and the population-level covariance matrix $\boldsymbol{\Omega}$. The Hierarchical Bayes (HB) method is employed to estimate these parameters. This method improves the stability of individual-level preference estimates by leveraging both the individual's historical choices and the choices made by other individuals in the dataset.

The coordinated routing system keeps a record of each driver's past routing decisions. To ensure that the estimated parameters remain up to date, we use each driver's most recent choices for parameter estimation. We denote the number of historical choices used for this purpose by H. Let $\mathbf{d_n} = (d_{n1}, \cdots, d_{nH})$ represent the historical routing choices of driver n, where d_{nt} indicates the choice made by driver n at time t, with $t = 1$ being the most recent and $t = H$ being the least recent.

Given the properties of the logit model, the probability of observing driver n 's choices $\mathbf{d_n}$ conditional on $\boldsymbol{\theta}_\mathbf{n}$ is expressed as follows:

$$P(\mathbf{d_n} \mid \boldsymbol{\theta}_\mathbf{n}) = \prod_{t=1}^{H} \frac{\exp\left(\boldsymbol{\theta}_\mathbf{n}^T \mathbf{x}_{\mathbf{d_{nt}nt}}\right)}{\sum_j \exp\left(\boldsymbol{\theta}_\mathbf{n}^T \mathbf{x}_{\mathbf{jnt}}\right)}$$

The probability of $\mathbf{d_n}$ given $\boldsymbol{\mu}$ and $\boldsymbol{\Omega}$ is formulated as follows:

$$P(\mathbf{d_n} \mid \boldsymbol{\mu}, \boldsymbol{\Omega}) = \int_{\boldsymbol{\theta}_\mathbf{n}} P\left(\mathbf{d_n} \mid \boldsymbol{\theta}_\mathbf{n}\right) f(\boldsymbol{\theta}_\mathbf{n} \mid \boldsymbol{\mu}, \boldsymbol{\Omega}) d\boldsymbol{\theta}_\mathbf{n}$$

Here, the function f represents the normal probability density function.

Our objective is to derive the joint posterior distribution of the parameters to be estimated: $\boldsymbol{\mu}, \boldsymbol{\Omega}$ and $\boldsymbol{\theta}_\mathbf{n}$ $\forall n$. By applying Bayesian theory and the derived conditional probabilities, the joint posterior distribution of these parameters is given by:

$$K(\boldsymbol{\mu}, \quad \boldsymbol{\Omega}, \boldsymbol{\theta}_\mathbf{n} \ \forall n \mid \mathbf{d_n} \ \forall n) \propto \left[\prod_{n=1}^{N} P\left(\mathbf{d_n} \mid \boldsymbol{\theta}_\mathbf{n}\right) f(\boldsymbol{\theta}_\mathbf{n} \mid \boldsymbol{\mu}, \boldsymbol{\Omega})\right] k(\boldsymbol{\mu}) k(\boldsymbol{\Omega})$$

In this context, $k(\boldsymbol{\mu})$ and $k(\boldsymbol{\Omega})$ represent the prior distributions of the population-level parameters. If no prior knowledge is available, a non-informative prior can be used to formulate the posterior distribution.

However, this posterior distribution lacks a closed form and must be approximated via simulation. To obtain samples from this posterior, we use Gibbs sampling [37], an iterative Markov Chain Monte Carlo (MCMC) method that generates a sequence of samples from the joint probability distribution of multiple random variables when direct sampling is challenging. In particular, we employ a three-step Gibbs sampling technique known as the Allenby-Train procedure [35] to derive the posterior samples.

- Step1: Drawing $\boldsymbol{\mu}$ conditional on $\boldsymbol{\Omega}$ and $\boldsymbol{\theta}_\mathbf{n}$ $\forall n$, using a normal Bayesian update with unknown mean and known variance.
- Step2: Drawing $\boldsymbol{\Omega}$ conditional on $\boldsymbol{\mu}$ and $\boldsymbol{\theta}_\mathbf{n}$ $\forall n$, using a normal Bayesian update with known mean and unknown variance.
- Step3: Drawing $\boldsymbol{\theta}_\mathbf{n}$ $\forall n$ conditional on $\boldsymbol{\mu}$ and $\boldsymbol{\Omega}$, following a Metropolis-Hastings algorithm. For more details, the reader can refer to [35].

Further details about the sampling process can be found in [28] and [35]. The posterior mean obtained from this sampling procedure is used as the estimate for each parameter. The estimated utility parameter for driver n, $\widetilde{\boldsymbol{\theta}_{\boldsymbol{n}}}$, is derived from the posterior mean of $\boldsymbol{\theta}_{\mathbf{n}}$.

4. Numerical Results

In this section, we conduct simulations to validate the effectiveness of the proposed method. We begin by detailing the experimental setup, followed by an analysis of how the method's solutions respond to changes in the number of clusters, number of OD pairs and the system's budget. We also emphasize the significance of the personalized incentive distribution algorithm by comparing it with scenarios where this algorithm is absent.

4.1 Experiment setup

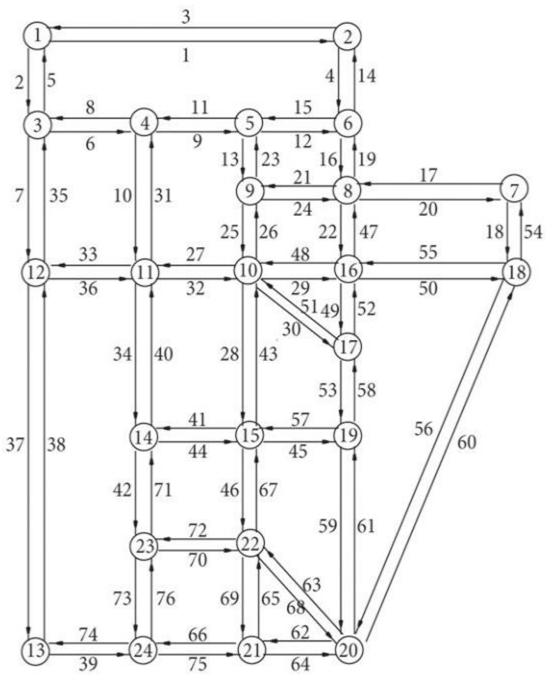

Figure 2. The Sioux Falls network.

In this study, a numerical simulation approach was employed to model the system dynamics. Unlike microscopic traffic simulations, this method focuses on solving mathematical models using numerical techniques. The details of the numerical simulation setup, including the specific parameters and algorithms used, are outlined below. We use the Sioux Falls network, a well-known benchmark in transportation research [38], consisting of 24 nodes and 76 links. The layout of the Sioux Falls network is depicted in Figure 2. We assume that the volume of passenger vehicles on each link remains constant.

For our analysis, we set $L = 3$, which means we consider three observable attributes in drivers' routing decisions: estimated current travel time, distance, and maximum historical travel time of a route. The utility function for driver n is expressed as $U_{jn} = \theta_n^1 x_{jn}^1 + \theta_n^2 x_{jn}^2 + \theta_n^3 x_{jn}^3 + p_{jn} + \beta_n \epsilon_{jn}$, where x_{jn}^1, x_{jn}^2, and x_{jn}^3 represent the estimated current travel time (in minutes), distance (in miles), and maximum historical travel time (in minutes), respectively. The maximum historical travel time captures the highest recorded travel time over the past 25 periods, reflecting delays due to incidents or high demand. Driver n 's utility parameters, $\boldsymbol{\theta}_{\mathbf{n}} = (\theta_n^1, \theta_n^2, \theta_n^3)$, correspond to these attributes. In our simulation, we created a pool of 2500 drivers, with utility parameters sampled from a normal distribution $\boldsymbol{\theta} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Omega})$, where $\boldsymbol{\mu} = \{-1.31, -0.63, -0.25\}$ and $\boldsymbol{\Omega}$ is $\{[0.080, 0.0030, 0.0005], [0.0030, 0.039, 0.0010], [0.0005, 0.0010, 0.018]\}$.

In the Sioux Falls network, we designate 10 OD pairs for truck drivers: (1,7), (1,11), (10,11), (10,20), (15,5), (24,10), (15,7), (24,8), (13,2), and (13,7). Each OD pair is assumed to have three alternative routes. For each period, the demand for these OD pairs is randomly drawn from a normal distribution. After the demand is established, a corresponding number of drivers is randomly chosen from the driver pool and assigned to the respective OD pairs.

We solve optimization problems ([obj1]) and ([obj2]) using the interior point method, using the fmincon solver from the Matlab optimization toolbox [39]. To estimate the parameters of the logit mixture model, we use a Markov Chain Monte Carlo (MCMC) algorithm implemented with the RSGHB package in R [40]. This procedure runs a single chain for 10,000 iterations, discarding the first 10,000 iterations as burn-in to ensure convergence.

4.2 Model performance and sensitivity analysis

In all experiments, we evaluate performance using a weighted combination of the total travel time for passenger vehicles and the negative value of the total utility derived by truck drivers. This metric, where smaller values of Y indicate better system performance, is represented as follows:

$$Y = \lambda T - (1 - \lambda) U$$

In this context, T refers to the total travel time for passenger vehicles, and U denotes the total utility for truck drivers. For the experiments that follow, we use a weighting factor λ set at 0.2.

We assess the performance of the coordinated routing system by comparing it to the UE scenario, focusing on the differences in the performance metric. To calculate the metric for the UE scenario, we use the simulated user equilibrium introduced in Algorithm 2, applying the drivers' actual utility parameters. The simulation parameters for simulation are set to $\eta = 0.1, M = 100$, and $\tau = 2\%$. In the greedy incentive distribution heuristics, the error margin ξ is defined as $\tilde{\beta} + \frac{B}{2|\mathcal{D}|}$, where $\tilde{\beta}$ is the population-level mean of β, and $|\mathcal{D}|$ represents the number of truck drivers in the period.

To assess the performance of the coordinated routing system, we examine the actions of individual drivers. Each truck driver receives their route assignment and corresponding incentive (a_n, p_n), along with details about the assigned route and the UE route. Drivers evaluate the utility of the assigned route against the utility of the UE route, $U_{co,n}$ versus $U_{ue,n}$, to decide whether to accept the assigned route. The participation rate is calculated based on the number of drivers who follow their assignments. Drivers who choose not to comply are assumed to select the most beneficial route from the available alternatives. The final performance metric is then computed based on these route selections. In addition to this metric, we also calculate the actual financial balance of the central coordinator, considering that only drivers who follow their assigned routes will incur payments or charges.

In our experiments, the coordinated routing system is tested over multiple periods, each with randomly generated demand for each OD pair. The initial periods function as a data collection phase, where drivers' responses are recorded to estimate utility parameters. The system's performance is evaluated over the final 25 periods, with the results averaged across these periods. As the accuracy of parameter estimation improves with the accumulation of each driver's historical choices, we examine scenarios with different volumes of historical choice data per driver, assessing their impact on participation rates and the overall performance metric. Additionally, we compare these scenarios to an ideal case where there is no estimation error, and the coordinator has access to the actual utility parameters of the drivers. This comparison allows us to evaluate the influence of estimation errors on system performance.

Next, we assess the performance of the proposed algorithm and examine its sensitivity to several key parameters: the number of OD pairs (W), the number of clusters (K), the coordinator's budget (B), and the volume of historical responses from each driver. To streamline our analysis and avoid confusion from varying parameter sets, we establish a baseline scenario and then modify one parameter at a time. For the baseline scenario, the following parameters are used: the number of OD pairs $W = 6$, the number of clusters $K = 6$, a coordinator budget $B = 0$, and 50 historical choice records per driver.

Table 2. Sensitivity to the volume of drivers' historical choice records (6 OD pairs, 6 clusters, 0 budget).

volume of drivers' historical choice record	drivers' compliance rate	coordinated routing metric	UE metric	metric decrease %	system's actual revenue
no estimation error	98.2%	12827.99	13340.70	3.82%	13.47
200 historical records	74.1%	12937.32		3.02%	184.35
100 historical records	70.5%	12973.52		2.75%	121.91
50 historical records	63.9%	13019.29		2.41%	47.87
30 historical records	57.5%	13048.13		2.19%	-206.99

Table 2 shows the system's performance with different volumes of drivers' historical data. In these experiments, we set the number of OD pairs to 6, the number of clusters to 6, and a system budget of 0. The first row of the table shows an ideal case where the central coordinator has direct access to each driver's true utility parameters, serving as a benchmark to assess the impact of utility parameter estimation errors. This row demonstrates that nearly all drivers follow their assigned routes when there are no estimation errors. Conversely, the last row indicates that when historical data is limited, the driver compliance rate falls below 60%, resulting in the system's actual financial balance not meeting the budget.

As the volume of historical data grows, the accuracy of utility parameter estimation improves. This enhanced precision enables the system to offer more accurate and attractive route assignments and incentives. Consequently, a larger historical data volume results in a higher participation rate and a lower metric, signifying an overall improvement in the system's performance.

Table 3. Sensitivity to the number of OD pairs (6 clusters, 0 budget, 50 historical choice records).

number of OD pairs	percentage of trucks in the network	drivers' compliance rate	coordinated routing metric	UE metric	metric decrease %	system's actual revenue
4	11.1%	60.9%	9772.67	9980.57	2.08%	85.97
6	16.3%	63.9%	13019.29	13340.70	2.41%	47.87
8	19.8%	64.0%	16933.21	17418.86	2.79%	282.36
10	22.3%	62.0%	20424.13	21048.25	2.96%	154.63

Table 3 explores the system's response to increases in both the number of OD pairs and truck volume. In these experiments, the number of clusters is set to 6, the system budget is 0, and each driver has 50 historical records. Although the participation rate exhibits slight variations, a higher number of truck OD pairs results in more significant improvements achieved by the coordinated routing system. This improvement is attributed to the increase in OD pairs, which expands the number of links affected by truck traffic, enabling the proposed algorithm to more effectively distribute traffic loads across these links.

Table 4. Sensitivity to the number of clusters (6 OD pairs, 0 budget, 50 historical choice records).

number of clusters	drivers' compliance rate	coordinated routing metric	UE metric	metric decrease %	system's actual revenue
4	58.9%	13043.20	13340.70	2.20%	46.90
6	63.9%	13019.29		2.41%	47.87
8	65.5%	12982.50		2.69%	295.99
10	66.8%	12970.76		2.77%	366.66

Table 4 shows the system's performance with varying numbers of clusters. In these experiments, the number of OD pairs is set to 6, the system budget is 0, and each driver has 50 historical records. Increasing the number of clusters in the route assignment problem positively impacts both participation rates and overall system efficiency. By grouping drivers into more refined categories based on their preferences, the cluster-based route assignment aligns better with individual utility parameters, thus improving compliance and system performance. However, a larger number of clusters also leads to longer computational times.

Table 5. Sensitivity to the system budget (6 OD pairs, 6 clusters, 50 historical choice records).

system's budget	drivers' compliance rate	coordinated routing metric	UE metric	metric decrease %	system's actual revenue
0	63.9%	13019.29	13340.70	2.41%	47.87
400	76.6%	12955.07		2.89%	-284.24
800	82.3%	12927.21		3.10%	-561.94
1600	87.2%	12897.58		3.32%	-1189.72

Table 5 shows the system's performance when the coordinator is allowed a positive budget. In these experiments, the number of OD pairs is set to 6, the number of clusters to 6, and each driver has 50 historical records. On average, there are 1900 drivers per period. It is reasonable to anticipate that increasing the system's budget would boost the compliance rate, thereby enhancing overall system performance. The experiments confirm that the system's average actual payment remains below the allocated budget.

4.3 The necessity for personalized incentives

This subsection highlights the advantages of personalized incentives over cluster-based incentives. Table 6 presents a comparison between the performance of incentives produced by the personalized incentive distribution algorithm, as described in Section 3.3, and those obtained from the optimization problem detailed in Section 3.2.

Table 6. Comparison between personalized incentives versus cluster-based incentives (6 OD pairs, 6 clusters, 0 budget).

volume of drivers' historical choice record	personalized incentives			cluster-based incentives			UE metric
	drivers' compliance rate	coordinated routing metric	system's actual revenue	drivers' compliance rate	coordinated routing metric	system's actual revenue	
200 historical records	74.1%	12937.32	184.35	65.1%	13163.24	-728.88	13340.70
100 historical records	70.5%	12973.52	121.91	64.9%	13203.00	-1087.45	
50 historical records	63.9%	13019.29	47.87	66.7%	13229.77	-463.66	
30 historical records	57.5%	13048.13	-206.99	64.3%	13296.58	-556.07	

This analysis emphasizes the critical role of personalized incentives, as derived in Section 3.3, in enhancing compliance rates and overall system performance. According to the table, personalized incentives result in an average metric reduction of 2.59%, whereas cluster-based incentives achieve only a 0.87% reduction. It's noticeable that although cluster-based incentives contribute to improving the metric, they do not align with the system's budgetary goals. Personalized incentives, by addressing individual driver preferences more effectively, ensure higher satisfaction and better adherence to the routing system.

5. Conclusion

This study presents an innovative coordinated freight routing system that adapts to drivers' utility functions, which are learned from their recent routing choices. By employing a logit mixture model and a Hierarchical Bayes estimation method, the system continuously aligns route assignments and incentive distributions with the evolving preferences of individual drivers. The experimental results demonstrate significant improvements in network efficiency, with most truck drivers opting to follow the assigned routes, even under budget-neutral conditions.

The success of this system in managing freight traffic suggests that similar approaches could be applied to other traffic segments, such as commuter vehicles or public transportation. The personalized incentive model could be adapted to encourage the use of environmentally friendly routes or off-peak travel times, contributing to broader sustainability goals. Moreover, by reducing congestion, the system can positively impact urban air quality and overall public health, addressing some of the pressing challenges in urban planning and environmental management.

Future research could explore several avenues to enhance and expand the system. First, incorporating real-time traffic fluctuations, such as those caused by accidents or sudden changes in weather conditions, would improve the system's responsiveness and reliability. Additionally, integrating machine learning techniques to predict traffic patterns and adjust incentives accordingly could further optimize the system's performance. Another promising direction is the application of distributed optimization techniques to handle larger and more complex transportation networks. As urban areas continue to grow, scaling the system to accommodate increased traffic volumes and more diverse routing preferences will be crucial.

In conclusion, this study contributes a robust and adaptable framework for coordinated freight routing, with the potential to significantly enhance urban transportation efficiency. By addressing the challenges and exploring the future research directions outlined, this system could play a key role in the evolution of smart transportation networks, paving the way for more sustainable and efficient urban mobility solutions.

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Data Summary

Products of Research

The traffic flow data from Caltrans Performance Measurement System (PeMS) were collected for the study to determine the parameters in the BPR functions.

Data Format and Content

Data is in the format of zip file and includes following traffic information: timestamp, sensing station identifier, direction of travel, lane type, station length, total flow, average speed.

Data Access and Sharing

The general public can access the data through website https://pems.dot.ca.gov/.

Reuse and Redistribution

The data can be reused and redistributed by the general public through website https://pems.dot.ca.gov/.

Appendix

This appendix introduces the derivation of the user equilibrium using a cluster-based method. In a UE scenario, drivers independently choose their routes. It is recognized that multiple, non-equivalent UE solutions can exist. In this study, we identify a UE solution that minimizes a weighted combination of the expected total travel time for truck drivers and the negative value of their expected total utility. This method allows us to derive a cluster-based UE for the route assignment problem outlined in Section 3.2. To achieve this, we solve the following optimization problem, which incorporates complementary constraints [41]:

$$\begin{aligned} \underset{\mathbf{A},\mathbf{\Phi}}{minimize} \quad & O(\mathbf{A}) \\ s.t \quad & 0 \leq \alpha_k^{w,r} \perp \delta_k^w \geq \mathbf{x_{rw}}(\mathbf{A})^T\ \bar{\boldsymbol{\theta}}_\mathbf{k}^\mathbf{w}\ \forall w,k,r \\ & \sum_r^R \alpha_k^{w,r} = 1 \qquad \forall w,k \end{aligned}$$

where δ_k^w is a set of free variables and the notation $\perp$ means that $\alpha_r^{w,k} = 0$ or $\delta_k^w = \mathbf{x_{rw}}(\mathbf{A})^\mathrm{T}\ \bar{\boldsymbol{\theta}}_\mathbf{k}^\mathbf{w}$. Note that the free variables δ_k^w are employed only in the complementarity constraints, which is a common technique utilized in many similar problems.

At the UE, the expected utility of cluster k in od pair w is represented as follows:

$$Q_k^w = \sum_r^R \alpha_k^{w,r} \left(\mathbf{x_{rw}}(\mathbf{A})^T\ \bar{\boldsymbol{\theta}}_\mathbf{k}^\mathbf{w}\right)$$