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A Promising Distance-Based Gasoline Tax Charging System Based on Spatio-Temporal Grid Reservation in the Era of Zero-Emission Vehicles

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Abstract

Fuel taxes are still a primary funding source for the development and maintenance of transportation infrastructure. Such a tax is collected as a flat fee from the importer or producer of the taxable fuel product. Fuel-efficiency improvements and the adoption of zero-emission vehicles result in a continuous decrease in gasoline tax revenues. This paper proposes a novel distance-based alternative method to replace current gasoline tax collection systems in Japan by providing a software architecture platform. In this platform, we utilize driving information gathered via communication mechanisms installed in connected automated vehicles to develop a system that collects gasoline tax based on reserving spatio-temporal grids. Spatio-temporal sections are created by dividing space and time into equal grids and a designated tax charge is assigned. Connected automated vehicles reserve a planned travel route in advance and travel based on reservation information. The performance evaluation results indicate that the proposed system adequately reserves the requested grids and accurately collects gasoline taxes based on a spatio-temporal grid with minimum communication time and no data package loss. The proposed method is based on micro travel distance charges, which generates gasoline tax revenue by 5.7 percent for model year 2022 and 21.8 percent for model year 2030 as compared to the current flat-fee system.

Keywords

Automated Vehicle, Zero-Emission Vehicle, Gasoline Tax, Micro-Road-Pricing, Spatio-Temporal-Grid

1. Introduction

The era of automated, connected, and electric vehicles is exploding. Extensive worldwide research efforts over the last two decades have resulted in sufficiently reliable, affordable, and popular products [1]. According to the results of the 2015 World Economic Forum survey of cities around the world, nearly 60% of consumers are willing to commute in self-driving vehicles [2]. The revolutions of electrification, automation, and sharing create new challenges for major revenue sources in transportation infrastructure.

Based on Bloomberg's Electric Vehicle Outlook, the annual publication for the world of electric vehicles, predicts that by 2040, AVs (Autonomous Vehicles) will account for 50% of all vehicle sales, 30% of vehicle ownership, and 40% of all vehicle commutes [3]. In order to advance innovation and maintain global market competitiveness, the automobile industry invested approximately 103 billion dollars in R & D in 2020 [4]. With optimistic announcements made by some organizations and successful testing and launching of autonomous vehicles by Tesla, Google, Waymo, Toyota, Honda, and others, commercialization and greater adoption of autonomous vehicles are accelerating [5].

Based on the OECD/ITF (International Transport Form) report, they predicted that when more zero-emission cars are adopted, gasoline tax revenue will decrease by 56% between 2017 and 2050. This is mainly due to improvements in fuel efficiency and the adoption of zero-emission vehicles with respect to the increase in demand for vehicles [6]. As well, the United States Environmental Protection Agency (EPA) reports that vehicle fuel consumption efficiency will improve from 35 to 54.5 mpg based on corporate average fuel economy standards (CAFE) for model years 2017 to 2025 [7]. Several studies and publications have highlighted the shortfalls in gasoline tax revenue, particularly when high fuel-efficiency vehicles are adopted. Alan Jenn *et al.* studied the revenue generation for the state of Colorado in the United States and warned that annual gasoline tax revenue will decline by 2025 due to the adoption of zero-emission vehicles [8]. Japan's gasoline tax supports the development and maintenance of its transportation infrastructure. According to the national tax agency (NTA), gasoline tax revenue continuously decreased from 2010-2020 [9]. Fuel tax revenue is decreasing as fuel efficiency improves and zero-emission vehicles are adopted.

To find a solution for obtaining sustainable gasoline tax revenues, various researchers are investigating a flat annual fee, a vehicle's manufacturer's retail price, and vehicle mile travel methods. Many of the proposed methods have drawbacks and cannot address the emerging challenges. Certain research studies show that vehicle mile travel is a promising alternative method to replace the current flat-fee gasoline taxation methods. Since the VMT tax is a relatively new concept and still in the experimental stage, less is known about its actual impact on driving behaviors, tax revenues, and tax burden.

Alan Jean *et al.* investigate a flat annual registration fee and the study suggests a flat annual registration fee of 0.6% of the vehicle's manufacturer's retail price

(MSRP). Furthermore, they estimated a 22-cent per mile fee to overcome the decrease in revenue for the USA. McMullen *et al.* (2010) find that a VMT tax (set at 1.2 cents per mile) that replaces a 24-cents-per-gallon gasoline tax would be slightly more regressive than the fuel tax [10]. Robitaille *et al.* compare a $0.015 VMT tax with a $ 0.10 federal gasoline tax increase and conclude that the former leads to a larger decrease in consumer surplus and a loss of social welfare.

In 2013, the first pilot project for a mileage-based revenue system was implemented in Oregon, USA. They installed the GPS tracking device on voluntary vehicles (limited to 5000 automobiles and light-duty commercial vehicles in the initial phase) at a cost of $250 per vehicle. Each vehicle was charged a tax of 1.5 cents per mile on their traveled distance on public roads. Participants in the scheme got monthly invoices for their road-use costs and had the state fuel tax repaid when they bought gasoline at Oregon stations. As a result, it is a complicated system for both users and authorities to implement on a large scale and with less accuracy for assigning gasoline tax charges. Furthermore, it is difficult to distinguish between travel in the different provinces or states and calculate the tax revenue for each type of vehicle in many provinces or states.

The University of Iowa's public policy center conducted a 2-year field study to evaluate the technical feasibility and user acceptance of mileage-based charging systems. In this research, technical feasibility problems included on-board unit installation, tax calculation accuracy, and fee evasion. They were able to track approximately 92.5 percent of all traveled miles using GPS and onboard vehicle devices. The remaining driven miles were estimated from the car's odometer using an interpolation technique, which will have an impact on revenue collection by not registering and calculating driven miles for each vehicle type. The second part of the study results shows that 71% of the participants preferred auditability and maximum privacy protection when using the system.

The most significant component for people's acceptance of the new system is determining an acceptable tax price for each vehicle type via the VMT method, which is one of the barriers to overcome [11]. Since all studies suggest a flat fee per mile, it raises further equality problems and challenges the willingness to adopt the new tax system. Furthermore, in terms of fuel consumption and road occupancy, there are various types of vehicles. A flat fee levied as a tax on all types of vehicles is provoking equity concerns regarding willingness to change to the new system. Each type of vehicle consumes a different amount of fuel for commuting 100 km and has various types of fuel efficiency, such as cars, buses, trucks, hybrid vehicles, electric vehicles, hydrogen, solar energy, etc. Furthermore, as each vehicle occupies a distinct section of the road, it is not appropriate to compare the road damage of a small passenger vehicle to that of a truck. which is an equity concern regarding road maintenance fees charged for each type of vehicle.

When modelling the effects of a VMT tax or any other alternative method, it is essential to consider how drivers will respond to dynamic changes in the tax structure and driving prices for each type of vehicle. However, since the vehicles have different fuel consumption and various types of energy use, in all studies, they found that drivers preferred auditability and maximum privacy protection to understand their daily usage. Furthermore, because each state has different tax regulations, an intelligent system that levies charges for different states when a vehicle travels between states is required. Moreover, when vehicles travel between two states, the boundary may not always be exactly one mile or km to calculate accurately the fuel tax or road tax for a vehicle. Therefore, a system is needed that could be able to calculate the two-state different types of fuel tax charges and charge based on a minimum travel distance, as all travel distances could not be exactly one km or one mile.

To implement the distance-based charging system, collecting real-time traffic data, vehicle networking, and communication are the essential factors for implementing the new system. Moreover, to understand the distance traveled with high accuracy for each vehicle type, it is important to collect real-time data for all the vehicles. To impose the new gasoline tax system on those who try to manipulate the total distance traveled to avoid the tax. It is essential to collect real-time data on vehicles, and the vehicles reserve the route for driving. Human drivers may not strictly observe these traffic rules, but automated vehicles would easily do it. However, the new distance-based charging system could be implemented in any type of ordinary vehicle by installing a low-cost device equipped with GPS localization and a cellular-like communication (e.g., 4G) system. Although, because the future vehicle will be an automated and intelligent vehicle, and the new system will collect gasoline tax from zero-emission vehicles, we will consider an automated vehicle for this study. The vehicle's driving information is collected through communication methods installed in connected automated vehicles, which can cooperate to fulfill the essential factors to implement the proposed method.

Automated vehicles are sophisticated networks that collect data and communicate with their surrounding environment with high accuracy, which are expected to reduce traffic fatalities by replacing human drivers with self-driving technology using autopilot [12]. Automated vehicles utilize lidar, radar, and high-resolution cameras that operate as an independent in-vehicle unit to detect such nearby objects as road markings, infrastructure, automobiles, bicycles, and pedestrians [13]. To enable automated driving, the fundamental principle of automated vehicles is to travel from point A to B by navigating a state space. A state space is commonly described as an occupancy grid, which shows where vehicles are located in the environment [14]. In addition, such motion-planning techniques as graph search, sampling, interpolating, and numerical optimization generate optimal path planning based on collected data to travel from a starting point to a destination [15]. Currently, automated vehicles utilize advanced driving assistance systems (ADAS) that improve safety, comfort, travel time, and energy consumption [16].

Technologies like adaptive cruise control, automatic emergency braking, intelligent speed adaptation, lane keeping assist, lane departure warning, and lane change assist are the main assistance technologies that address longitudinal and lateral comfort, safety, and security [17]. Currently, ambiguous obstacle detection at high speeds over long distances is one of the most difficult technical challenges. Cameras can't see through fog, lidar can't interpret a driver's intentions, and detecting a human in the dark by machine learning is also challenging, although communications from vehicle to vehicle or vehicle to anything can convey information [18] [19]. If AVs act independently, then efficient and safe mobility will not be feasible. Instead, to achieve a cooperative environment, which is globally known as a connected automated vehicle (CAV), further connectivity is needed to advance safety [20].

A connected vehicle is a collection of applications, services, and technologies that enable the creation of such vehicular communications systems as vehicle-to-anything V2X, which includes vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication [21]. These vehicular communication technologies permit external support for computing tasks that mitigate traffic collisions and blind-spot detection by simultaneously exchanging such real-time state information as location, speed, acceleration, and direction among vehicles within a particular range [22]. In a smart travel system, communication and choosing an appropriate networking system are essential for response time in the reservations mechanism. However, depending on the application, two types of technologies are extensively utilized in vehicular networking communication: dedicated short-range communications (DSRC) IEEE 802.11p and cellular networks as third generation long-term evolution (2 - 3 GLTE). Both DSRC and cellular networks are currently collecting ETC highway tolls and providing weather, construction congestion awareness information, and parking assistance [23]. It is easy to collect real-time data and provide a response for reservations as well as detailed travel and tax information.

CAV technology improves the overall traffic flow and safety on freeways using heuristic algorithms and optimal control strategies that were developed for ramp-metering to regulate the flow of vehicles merging onto freeways to decrease traffic congestion and increase safety [24]. For safe and efficient autonomous control of traffic through intersections, coordination methods are used so that vehicles cross intersections (or merge) without rear-end or lateral collisions in the merging zone. Centralized [25] and decentralized [26] control algorithms or intersection managers coordinate the reservation or crossing schedules based on the received requests and information to improve traffic capacity. Since vehicular networking technology is developing so rapidly, connected vehicles will soon be integrated with 5G technology to optimize their cooperative efficiency, including the internet of things and heterogeneous access of networks [27]. These technological advancements, paired with the applicability of new methodology in automated vehicles, increase the feasibility of accurately implementing dynamic map systems for road reservation mechanisms based on the distance-based charging method.

In this paper, a novel dynamic distance-based gasoline tax charging system is proposed, aiming to collect gasoline tax revenue as an alternative to the current flat-fee method. We propose the vehicle's driving information through communication methods installed in connected automated vehicles, reserving a geographical space (several meters) and time (several seconds) and applying distance-based charges as an alternative tax to replace the current flat-fee gasoline tax collection method.

In summary, our contributions are as follow:

- The adoption of zero-emission vehicles has escalated, leading to a reduction in fuel tax revenue. It is critical to develop a system capable of collecting the gasoline tax in the zero-emission vehicle era.
- The tax issue is critical for vehicle owners in general, and an increase in the tax would present a new challenge to the willingness to transition to the new tax system. Therefore, a system is needed that does not change much in their ownership cost. Thus, based on the proposed design, a tax charge system comparison with the current method does not change much in the ownership cost of the vehicle.
- Tax charge accuracy is essential in terms of individual payments as well as total tax revenue for the government. Therefore, a system is needed that accurately collects the gasoline tax with high accuracy. The proposed method's performance evaluation result shows that the proposed method is able to collect gasoline tax with high accuracy with no data package losses.
- According to numerous studies, auditability and privacy are the two most important factors influencing willingness to change to the new gasoline method. As a result, we develop a system that provides auditability while also protecting the owner's privacy, with only specific data considered to be stored to protect the user's privacy.

This paper is organized as follows: in Section II, the proposed method structure and system module are presented. Section III describes our system's implementation. Section IV outlines its performance evaluation. Section V describes the results and discussion. Finally, in Section VI, we conclude and describe future work.

2. Related Work

Fuel tax is still collected as a flat-fee from all types of vehicles based on their fuel consumption as a specific percentage of the fuel price. Currently, no alternative system has been implemented for collecting gasoline tax based on vehicle miles traveled or any other method. The University of Iowa's public policy center conducted a 2-year field study to evaluate the technical feasibility and user acceptance of mileage-based charging systems for vehicles through such physical operations as installing on-board units (OBUs) and interviews and questionnaire surveys of various stakeholders [31]. In this research, technical feasibility problems included on-board unit installation, tax calculation accuracy, and fee evasion. As well, the questionnaire survey results show that when using the system, 71% of the participants preferred auditability and maximum privacy protection [28].

Several studies have examined its distributional implications and equity concerns. Zhang *et al.* (2009) estimate that Oregon's flat VMT tax would not lead to significant changes in the tax burden and taxpayers' welfare in either the short or long term [29]. Weatherford (2011) finds that a VMT tax, set at 0.98 cents per mile, would shift the tax burden from low-income to high-income households, from rural to urban households, and from retired to younger households with children [30]. The VMT tax would benefit rural households more than their urban counterparts because the vehicles owned by rural households are on average less fuel-efficient. Robitaille *et al.* (2011) compare a $ 0.015 VMT tax with a $ 0.10 federal gasoline tax increase and conclude that the former leads to a larger decrease in consumer surplus and a loss of social welfare [31].

Alan Jenn *et al.* studied the revenue generation for the state of Colorado in the United States, estimating that total annual revenue generation would decrease by about $200 million by 2025 as a result of EV adoption in our base case, but in projections with larger adoption of alternative vehicles, it could lead to revenue generation reductions as large as $900 million by 2025. A flat annual registration fee at 0.6% of the vehicle's manufacturer suggested retail price (MSRP) or 22 cent per mile fee as an alternative method to enhance the gasoline revenue. Since there are various types of vehicles, each with different sizes, fuel economy, and axel loads, both the MSRP and the per mile price may not be viable.

Rebecca Lewis and Benjamin Y. Clark investigate the revenue loss attributed to new mobility and evaluate revenue sources to fund transportation. They studied five Oregon cities, describing how transportation is currently funded and estimating revenue loss in a scenario of electrification, automation, and sharing using empirical analysis of local government budget data. They suggest that governments should seek out ways to find more stable revenues (VMT-based revenues) and move away from less stable revenues (motor fuel) [32]. Yiwei Wang and Qing Miao simulate the vehicle usage, tax burdens, and total tax revenues generated under a possible nationwide revenue-neutral flat VMT tax [33]. Caplan (2009) estimates a VMT tax (set at 0.3 cents per mile for cars and 1 cent per mile for light trucks) would decrease annual pollution emissions by 7% - 11%, suggesting a significant environmental benefit [34].

As mentioned earlier, VMT is at an early stage because there is no adequate mechanism being investigated as a replacement for the gasoline tax, such as a collection mechanism, dynamic pricing system, reducing administrative costs, preventing payment evasion, maintaining privacy, and vehicle onboard equipment installation. However, utilizing the tollgate on all roads is one of the options to collect gasoline tax, but the system has many drawbacks, including violation processing, high operational cost, fixed infrastructure device dependency, and a large amount of electronic equipment that must be installed in every vehicle and on the road infrastructure. To summarize, In the current situation, the collection of gasoline tax are dependent on permanent fixed infrastructure devices, and a huge number of electronic devices must be installed in both vehicles and on all roads. Moreover, the deployment of tollgates on all roads is unfeasible due to the significant operational expenses associated with utilizing the equipment for accurately collecting road-pricing tax based on the vehicle mile travel method. Therefore, the proposed method provides a sustainable new mechanism of collecting gasoline tax as well as addresses many of the aforementioned challenges. In the following sections, we address the above concerns and describe our novel micro-road-pricing method based on reserving spatio-temporal grids.

3. Structure and System Model

This section presents the overall structure of the proposed system, which reserves (virtual) spatio-temporal sections of a road as grid/msec units in real time.

3.1. Micro-Road-Pricing

At present, road pricing refers to a fee determined for the use of a road, such as distance or time-based fees [35], toll roads, congestion charges [36], and taxes intended to discourage certain types of cars, such as fuel propellants or polluting automobiles [37]. In this paper we propose a radical new approach to replace the present gasoline tax collecting method, which reserves (virtual) spatio-temporal sections of the road in real time for road pricing. This idea refers to the reservation of a geographical space (several meters) and time (several seconds) as well as levying a designated charge on the space-time/grid unit for each type of vehicle. Although human drivers would struggle to precisely observe such complicated traffic rules to reserve space-time grids on the road and manage gasoline tax-related issues, automated vehicles can manage them simply. However, by installing a low-cost device equipped with GPS localization and a cellular-like communication (e.g., 4G) system in any type of ordinary vehicle, the new micro-road pricing system could be implemented with an additional cost.

3.2. Overview of Proposed Method

In this study, a configuration system platform was established that consists of a network operating center/server, a viewer/user, and a billing center. An automated vehicle assumes the role of a vehicles or user to transmit position and driving information collected from various sensors to the server. Each connected automated vehicle reserves a scheduled travel route and time on a dynamic map and travels based on the reserved information. When the automated vehicle starts to drive, it sends the desired departure time, vehicle ID, origin, and destination information to the server. The network operating center/server communicates with the connected vehicles and generates a database based on the collected information.

Since a dynamic map contains a spatio-temporal grid, by dividing time and space into equal grids, spatio-temporal grids can be reserved on the road in real time. It computes a dynamic travel distance by grid/millisecond unit and assigns a designated charge for each independent cell or grid, which is converted from the fuel consumption of each type of vehicle. The network operating center provides detailed information about the travel distance and related costs to the vehicle users. If the user does not pay the charges online, the billing center creates a monthly charge invoice and sends it to the vehicle owner. The viewer displays the dynamic map generated by the server and provides detailed travel and tax information to the vehicle user via an API, as shown in **Figure 1**. When the vehicle starts driving, it sends the user's information and requests to the network operating center to reserve the grid in the route as shown in number (1) of **Figure 1**. After that, when the server receives the request, it first checks the dynamic map for occupancy and decides for the reservation of the grid (2), and then responds to the vehicle with grid and route reservations as well as tax charges (3). When the vehicle arrives at the destination (4), the server sends the overall detailed travel and payment information (5). Additionally, it saves designated data (6). If the vehicle doesn't pay the tax charges, it will send the monthly bill to the vehicle owner (7) as illustrated in **Figure 1**.

A dynamic map is a platform that collects probe data such as vehicle position and speed information from various sensors in connected vehicles. The main criteria of real-time data collection and display, such as car reflection on the map, transmission, registration of vehicle information, and static map information, will be fulfilled by implementing the dynamic map platform, as studied by Netten, L. Kester *et al.* [38]. Due to the above advantages of the dynamic map platform, we created a web-based dynamic map to implement the proposed system. In **Figure 2**, the overview of the structure's architecture that reserves a grid-based charging method is illustrated.

3.3. Overview of Dynamic Map Application

We created a server environment in Node.js and a web application framework called Express to implement a dynamic spatio-temporal section on roads in a

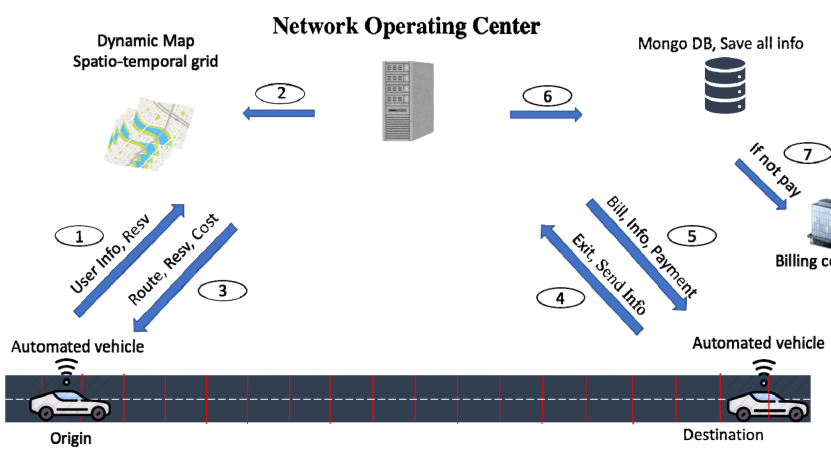

Figure 1. Sequence diagram of grid-based charging system.

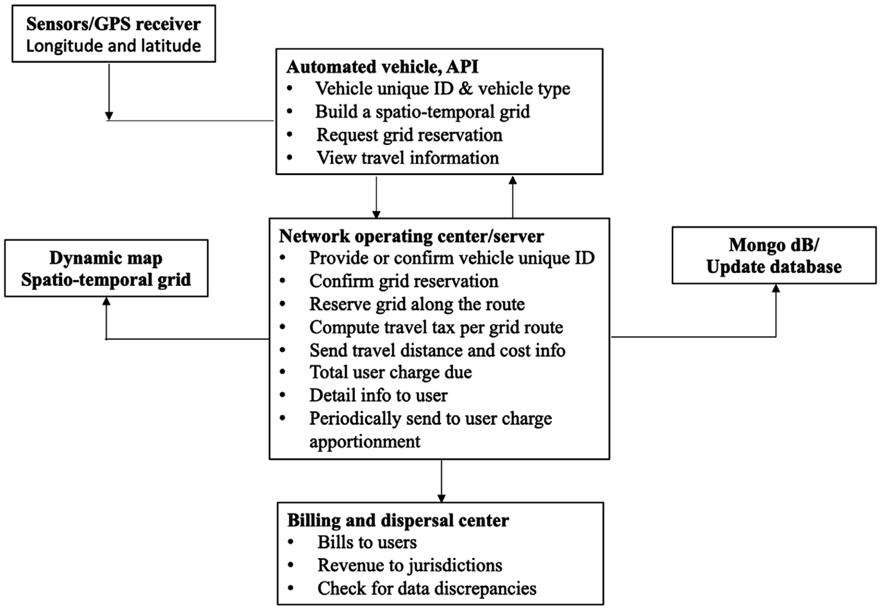

Figure 2. Structure architecture of reserving grid-based charging method.

real-time grid/millisecond unit-charging system. We developed spatio-temporal grids with MongoDB, a document-oriented database like the Relational Database Management System (RDBMS) that supports a nested document structure. A spatio-temporal grid resembles a collection of grids or cells created by equally dividing time into one millisecond intervals and space into latitude and longitude and expressed in a nested document structure. We created a one-kilometer straight road environment by equally dividing a space into a spatio-temporal grid and making independent cells.

The grid cell mechanism is shown in Figure 3. The white arrow represents the vehicle's traveling path, the gray cells indicate the reserved cells on the travel route, and the other cells indicate unreserved cells. Since we concentrate on cooperative autonomous vehicles, a vehicle must travel precisely during the reserved time and be able to communicate with its surrounding environment. Thus, the connected automated vehicle sends vehicle information to the server, such as the desired departure time, origin, and destination position. For the first time, if the system registers a new vehicle, the network operating center/server provides a unique ID number to each vehicle and verifies it on the dynamic map to reserve the requested space-time grid to respond to the vehicle. If the grid is occupied, then the server notifies the vehicle to pause (shown in red cell) and call back the request for reservation, as described in Figure 4. The server generates a database based on the information collected from all the vehicles; when a vehicle sends a request to reserve a grid, the server reserves the requested grid along the travel route.

3.4. Method of Assigning Cost to the Grid

As previously mentioned, the space is divided into equal grids, and designated

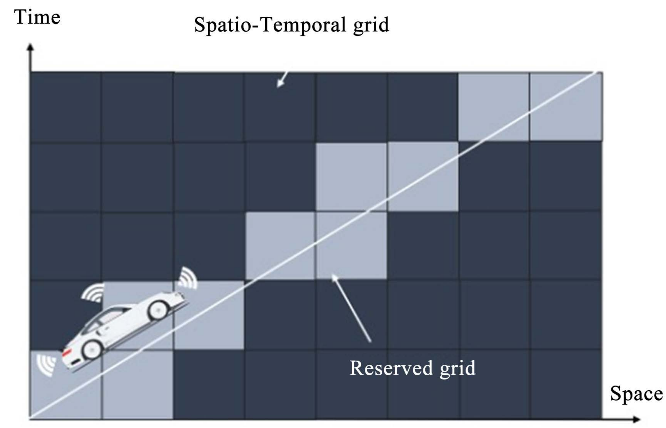

Figure 3. The reservation method of the spatio-temporal grid on a route.

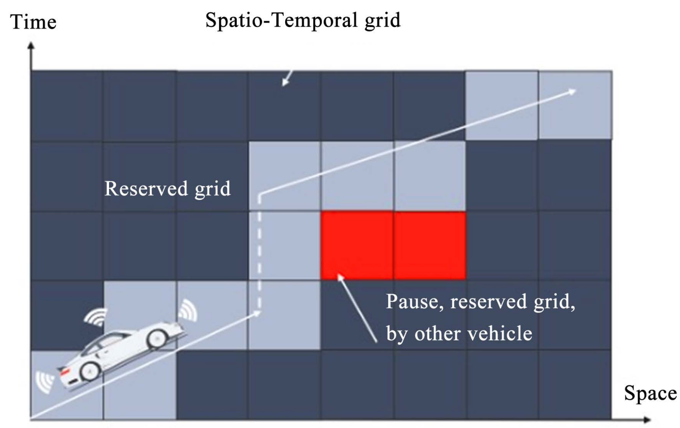

Figure 4. The mechanism of reservation of the spatio-temporal grid if the grid is reserved by another vehicle.

charges are allocated as the cost of each grid. When a vehicle submits a request to reserve the grid, the server assigns a designated tax charge to the grid for each type of vehicle and continuously calculates the tax costs for the travel route shown in Figure 5. Afterward, it records the vehicle information in MongoDB based on the vehicle's unique ID, date, time, travel distance, and calculated total tax charges for each type of vehicle. The billing center in turn creates monthly invoices and sends them to the vehicle's user if she does not use ETC or a credit card.

The assigned designated grid charge unit rate is converted from the fuel consumption efficiency of each type of vehicle to the grid/L from the CAFE standard. Based on the JAMA 2020 report [39], the fuel consumption efficiency rate for model year 2020 is 20.3 km/L, as estimated from the average fuel consumption of urban, rural, and express highways. The fuel consumption efficiency rate is converted into km/L and then grid/L units, multiplied by the 20% gasoline price, and assigned to each grid in the server's grid-based charging system. Following that, to create a grid/millisecond charge tax unit, the gasoline price is assumed to be constant at 1.5 $/L, where the government's gasoline tax revenue is 20% of the gasoline price per liter for each vehicle type, which is a combination

```
'2_0': { rcvID: 0, price: 0 },
'2_1': { rcvID: 0, price: 0 },
'2_2': { rcvID: 0, price: 0 },
'2_3': { rcvID: 0, price: 0 },
'2_4': { rcvID: 0, price: 0 },
'0_2': { rcvID: 0, price: 0 },
'1_2': { rcvID: 0, price: 0 },
'3_2': { rcvID: 0, price: 0 },
'4_2': { rcvID: 0, price: 0 },
```

Figure 5. Description example of spatio-temporal grid and assigning charges.

of 10% local and 10% national tax revenues assumed for this study. Additionally, the average fuel efficiency rate for each type of vehicle was created using different vehicle types, makers, and model years. Vehicles were classified into ten different categories, based on average fuel consumption from a combination of urban, rural, and express highways. The grid length could be any size, such as five meters, ten meters, or the length of various types of vehicles. It is possible to charge each type of vehicle based on its size and length, such as the length of a car, truck, and bus is approximately 4.6, 14, and 12 meters, respectively. For this study, we assumed the grid length to be five meters, which means 200 grids is one kilometer.

In this study, we only considered conventional gasoline cars and assumed that electric vehicles pay gasoline tax based on the travel distance in the proposed method, just like passenger cars. The tax charges are calculated based on this assumption and determined for both conventional gasoline cars and electric vehicles as illustrated in **Table 1**. A grid/millisecond (5m/millisecond) unit tax charge could also be created and expanded to every type of vehicle based on the same method for assigning designed tax charges in the proposed system. Thus, revenues can be captured from vehicles that do not use fossil fuels, such as electric cars or other zero-emission vehicles, for all vehicle categories.

4. Implementation

This section describes the implementation of our proposed method for reservations in a spatio-temporal grid-charging system.

4.1. Implementation Environment

The implementation environment of the proposed system is shown in **Table 2**. The server environment is Node.js, and the web application framework is Express. NodeJS is a JavaScript runtime execution environment for web servers that handle the back end of web development. Express is a minimal and flexible Node.js web application framework that provides a robust set of functionalities for web and mobile applications. This framework has the advantage of simplifying the description of numerous procedures for developing a web application with a variety of HTTP utility methods as well as the ability to establish a comprehensive API quickly and simply. The server was started on a Mac computer

Table 1. Conversion of fuel efficiency rate to grid (5 m/millisecond) for each vehicle type.

Vehicle types	Fuel economy rate km/L, 2020	Fuel economy rate L/1km	Space-time grid L/grid	Fuel price $/L, 2020	Fuel tax 20% $/L	Grid/msec unit price
Gasoline car	17.3 km/L	0.058 L/km	0.00029 L/G	1.25 $/L	0.25 $	0.0000725 $
Hybrid car	20.3 km/L	20.3 km/L	0.00025 L/G	1.25 $/L	0.25 $	0.0000625 $
Electric car	20.3 km/L	20.3 km/L	0.00025 L/G	1.25 $/L	0.25 $	0.0000625 $

Table 2. Implementation environment for the proposed system.

Environment	Model
OS	Mac OS Mojave 10.14.6
CPU	2.4 GHz Intel Core i5
Memory	8 GB
Python 3	COM interface
Server environment	Node.js + Express
Database	MongoDB version 4.0.4
PTV VISSIM 11	Traffic environment simulation
Load Test	Apache JMeter
Environment	Model

to ensure the proposed system's performance, and both HTTP requests and responses were validated in the local environment.

4.2. Application Programming Interface (API)

Figure 6 describes the flow chart of the reservation and cost assignment to the road or a grid. The network operating system/server enables vehicle users to apply for grid reservations to facilitate their driving. Thus, the server provides APIs to the automated vehicle users to make reservations on space-time grids using the POST method to reserve a travel route. The POST method transmits the vehicle's unique ID, scheduled departure time, origin's latitude and longitude, and destination position in the request body. After the server receives a request, it first queries the spatio-temporal grid database for an empty spatio-temporal grid in the travel route, then responds to the requested vehicle with grid and route reservations and calculates the route's cost. When the automated vehicle starts driving and continuously sends requests for grid reservations, the server dynamically reserves the grids and travel routesas illustrated in **Figure 6**.

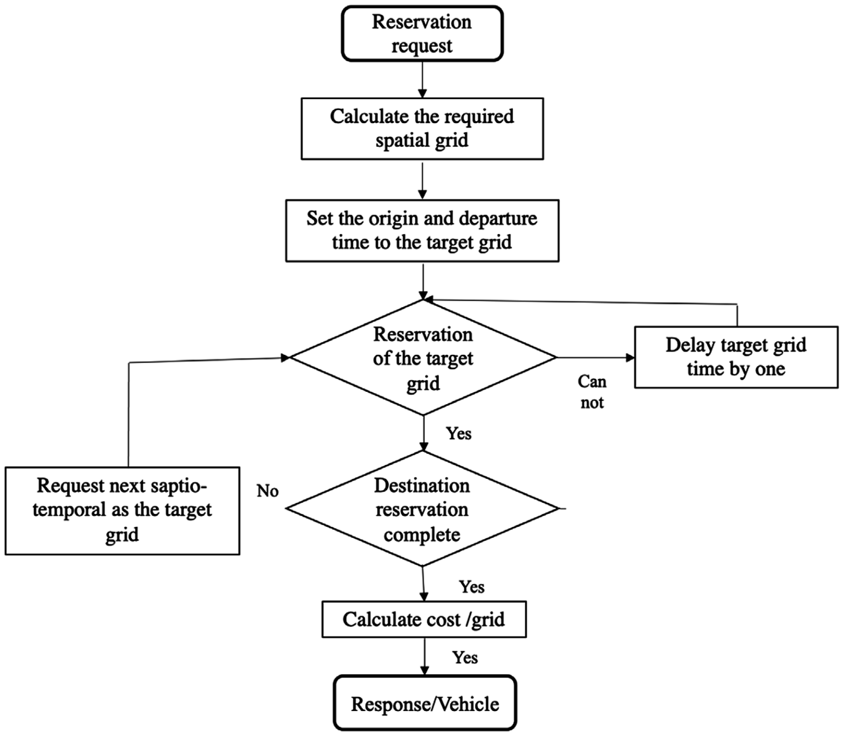

Figure 6. Flow chart of grid reservation and assigning cost processing of network operating server.

4.3. Spatio-Temporal Grid

MongoDB, which implements the spatio-temporal grid, is a document-oriented database, such as the Relational Database Management System (RDBMS) and is also open-source software. MongoDB does not save data in a table structure; it stores it in a JavaScript Object Notation (JSON) file format. JavaScript Object Notation (JSON) is a widely used open file and data interchange format which stores information in an organized and easy-to-access manner. The other beneficial quality is that it transmits data consisting of attribute-value pairs and array data types, which can be easily changed. Since the transportation infrastructure increases and decreases frequently, the space-time grid's data structure must also be frequently changed. Consequently, MongoDB is a schema-less database that is more flexible in terms of modifying the data structure after executing a system operation and enables a nested structure to store data. Thus, we manage our proposed system's spatio-temporal grid with MongoDB.

In this study, time is described in ISO Date type, which is divided into 1-millisecond intervals, and space is expressed in a nested document structure as latitude and longitude. A road's north-south direction (latitude) and east-west direction (longitude) are determined and controlled at regular intervals. When the vehicle reaches its destination, the server provides the user through the API with such detailed information as vehicle ID, travel time, travel distance, travel tax charges, and total tax charges as well safe data in Mongo DB as demonstrated in **Figure 7**.

Figure 7. Description example of storing data in MongoDB.

5. Performance Evaluation

5.1. Evaluation Environment

To evaluate the proposed method, we use three evaluation methods such as performance evaluation of the system, response time for the communication, and car ownership cost for both the grid-based charging system and flat-fee method.

First, we created a traffic environment in PTV VISSIM (Verkehr in Stadten-SIMulations Model) software, which is a microscopic multi-model traffic flow simulation software which can model a variety of types of traffic environments. Thus, we use it to model the traffic environment for the flow of passenger cars and electric cars. As well as the PTV VISSIM COM (Component Object Model) interface, which defines a hierarchical model in which the functions and parameters of the simulator allow you to externally design a model for any intelligence transportation system.

Second, we use PTV VISSIM 11, which supports the COM interface and can read script files written in any programming language. We developed a script file in the COM interface in Python that provides an environment for cooperative automated vehicles that communicate with the networking operator center/server. Thus, to execute the functions of the connected and automated vehicles, they send package data such as vehicle ID, origin position, and destination position to request a grid reservation through URLs to the server for each type of vehicle, as illustrated in Figure 8.

To implement the traffic environment as mentioned above we create a one-kilometer road with two-lane and 3.5-meter-wide. The number of vehicles on the road ranged from 100 to 500 vehicles per hour as a different vehicle input for simulation, and the vehicle speed limit was set to 60-kilometer meter/hour. Based on current global electric vehicle sales worldwide [40], the percentage of electric vehicles and passenger cars is assumed to be 1.6% and 98.4%, respectively, and the simulation measurement times were set to one hour as all the simulation parameters are illustrated in Table 3.

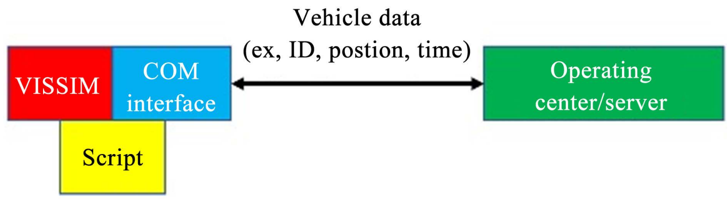

Figure 8. Demonstrate the environment developed for automated vehicles transmitting data to the network operating center.

Table 3. Simulation parameters for VISSIM.

Parameters	*Setting*
Speed limit	60 km/h
Number of vehicles (Sample)	500 veh/hr
Passenger vehicles: 2020-2030	98.4% - 80% = 492 - 400 vehicle
Electric vehicles: 2020-2030	1.6% - 20% = 8 - 100 vehicle
Lane width	3.5 m
Measurement time	1 hour
Number of measurements	10 times
Measurement section	1000 m
TTC (time-to-collision)	5.0 s

The measurement time is one hour, the number of measurements is ten times, and time to collision (TTC) is considered five seconds. To achieve the required 60 km/hr speed on one kilometer of road, we calibrated the software based on changes in the vehicle behavior and driving behavior parameters. Figure 9 shows the PTV VISSIM execution screen for the proposed method, where red and green cars represent conventional gasoline cars and electric cars.

5.2. Flow of Reservation and Assigning Cost to Grid

When an automated vehicle makes a grid reservation, perhaps other vehicles are simultaneously making reservations, which can cause inconsistencies and confusion. To avoid such issues, the server must process a vehicle's grid reservation requests on a first-come, first-served basis. Thus, Node.js provides non-blocking I/O asynchronous processing methods, which can process multiple requests with a single thread. Furthermore, to reserve a grid for each vehicle based on requests at a specific time, if the grid is already reserved by another vehicle, regaining access to the database is essential to process it once again. Therefore, a callback processing mechanism must be appropriately established. If the processing time is constant for requests and responses from the database, no inconsistency or overlapping will occur due to another vehicle's request for route reservations. This method of operation is faster than locking the database. In addition, when the server responds to a vehicle's grid reservation and the vehicle drives it successfully, the server assigns the charges to a grid that is driven on and saved in the MongoDB based on the vehicle's unique ID. When the server reserves the grid, it assigns the unique ID of the requested vehicle to the spatio-temporal grid, which is highlighted in red as illustrated in Figure 10. When the server reserves the grid, it assigns 1 as occupied and 0 demonstrate as unreserve grid.

5.3. Load Test

We conducted load tests to analyze the system's response time using Apache JMeter, an open-source Java application that tests load, functional behavior, and application performance. The response time is the period between when the cooperative autonomous vehicle sends a request and receives a response from the server. An HTTP request protocol is utilized that contains the vehicle ID, desired departure time, origin, and destination positions, which are contained as 5-space grids in the X direction and 5-space grids in the Y direction. We assumed that a cooperative automated vehicle could drive at 1 grid/millisecond and the desired departure time is identical for all the requests. The starting point is (0, 2) or (2, 0), and the destination is (2, 4) or (4, 2). The load test begins with the server in an unreserved state, and the results are obtained three times for such numerous requests as 1, 10, 15, and 50 in a loop. The load test results in Table 4 include average, maximum, and standard deviation of response times for each number of requests.

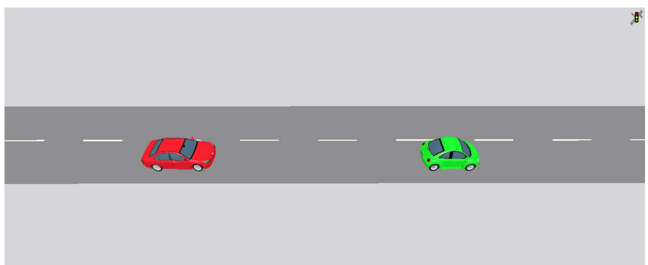

Figure 9. Execution screen of VISSIM simulation for proposed method.


```
_id: ObjectId("6061842e3ee61e4990d1a6a6")
time: 2021-03-29T07:39:28.597+00:00
space: Object
    2_0: 0
    2_1: 0
    2_2: 0
    2_3: 0
    2_4: 1
    0_2: 0
    1_2: 0
    3_2: 0
    4_2: 0
station: ObjectId("6061842ecee348f8bcd7ad01")
```


Figure 10. Description example of spatio-temporal grid reservation.

Table 4. Measurement of required times for requests and responses.

Number of requests	Response Time		
	Mean	Max	SD
1	41	41	0
10	33	46	7
15	36	58	11
50	43	48	10

5.4. Confirmation of Package Data, Accuracy, and Privacy

To clarify whether the proposed method is operating accurately, PTV VISSIM 11 provides an environment for cooperative automated vehicles that communicate with the networking operator center/server. In addition, PTV VISSIM supports the Component Object Model (COM) interface, which can read script files written in any programming language and send data from VISSIM to the server. Thus, script files were developed in Python 3 to execute the functions of the connected and automated vehicles to send package data such as vehicle ID, origin position, and destination position through URLs to the server for each type of vehicle.

First, we validated the required speed of 60 km/hr on the road in VISSIM based on changes in the vehicle behavior and driving behavior parameters. Subsequently, we ran the simulation and input various numbers of cars, such as 100 - 500, and checked the number of vehicles assigned from VISSIM to the network operating center database. We verified in the database all the assigned parameters, including the calculated distance, tax charges, and the number of invoices submitted to the billing center. If 100 vehicles make grid reservation requests from VISSIM, the server reserves grids and routes for all 100 vehicles, accurately calculates the travel distance, applies the designated charges, and saves the information in its database. We repeated the same approach for different vehicle inputs and verified that our proposed method's performance was accurate.

We created a one-km straight road in VISSIM and confirmed the distance traveled and tax charges for each vehicle in the database as 1000 meters and \$0.0125 for Prius vehicles. Detailed information was provided to the vehicle owner at the end of each travel trip to verify and ensure the ability to minutely audit both travel and tax information. The gasoline tax revenue charged to all vehicles is verified in the (MongoDB) database to validate that all vehicles were charged and to collect the tax from each vehicle as shown in **Figure 6**. To protect user privacy, only the vehicle ID, travel distance, tax charges, and invoice number related information are disclosed to the billing center, and not all the location data is considered to prevent tracking travel information issues as shown in **Figure 11**.

```
_id: ObjectId("605b0d8d40c975cc70facc8c")
decisionTime: 2021-03-24T09:59:41.969+00:00
cost: 0.0125
number: 123
sid: 1
regAt: 2021-03-24T09:59:30.322+00:00
__v: 0
```


Figure 11. Description example of invoice to billing center.

6. Simulation to Compare Gasoline Tax Revenue Collection for Flat-Fee and Proposed Grid-Based Charging Method

6.1. Proposed Method

To determine the proposed method's effectiveness, we evaluated and compared the gasoline tax revenue for a vehicle using the current conventional flat-fee method with the grid-based gasoline tax charging method. The grid-based charging method is to pay the gasoline tax fee based on the distance you traveled, which is considered a minimum of a grid (5 meters/millisecond), and the proposed system can be able to charge gasoline tax on a grid basis for all vehicle types. The revenue is calculated for 500 vehicles sample and for one km of travel road for both methods in model years 2022 and 2030. PTV VISSIM 11 is a microscopic multi-modal traffic flow simulator that models various traffic environments and visualizes traffic phenomena with 3D graphics. We used it to simulate a real traffic environment for the proposed method as well as, provide an environment for the cooperative automated vehicles. Since PTV VISSIM 11 also supports the Component Object Model (COM) interface to read script files written in any programming language and can transmit data from VISSIM to the server. We developed a script file in Python 3 that performed the roles of the connected and automated vehicles to transmit package data to the server through URL for each type of vehicle, including vehicle ID, origin position, and destination position.

The simulation environment for the proposed method is identical to the one described in the evaluation environment section. As the new gasoline tax charges are illustrated in section D of the proposed method structure and system model, we considered three types of vehicles for our simulation. The conventional gasoline cars such as gasoline-powered cars, hybrids (gasoline and battery electric), and full-battery electric vehicles (BEV). The average fuel consumption is considered for each type of vehicle for the JAMA 2021 report. Since full electric vehicles do not use fuel, we considered them the same as hybrid vehicles.

In this study, the road length is set to one km, the departure time for all vehicles starts from zero, and the end time is measured from the destination position when the vehicle arrives at the 1000-m position. First, we ensured that if 100 vehicles make grid reservation requests from VISSIM, the server reserves the grids and routes for all 100 vehicles. Second, ensure that for various types of vehicles, the designated charges are applied accurately based on the driven distance, such as, a vehicle being charged $0.125 for one kilometer of travel, as an example is shown in **Figure 11**.

Moreover, to confirm that there was no data package loss, the database was checked to ensure that all the information was saved in the database without any data package loss. As demonstrated in detail in section (D) of the proposed method structure and system model, the unit rate of the designated grid charge unit rate is assigned $0.0000725 in the network operating center/server. The first scenario in the proposed method is gasoline tax revenue for the 2022-year model. In PTV VISSIM, the percentage of cars in 500 vehicles for model year 2022 is set at 64.2 percent, 35 percent, and 0.8 for conventional gasoline vehicles (combination of Conventional and Clean diesel vehicles), hybrids, and electric vehicles (combination of Plug-in hybrid, Electric, and Fuel cell vehicles), respectively [41]. The plug-in hybrid electric vehicle is considered the same as the BEV for this study. Following the above settings and parameters, the simulation ran for one hour, and overall, 500 vehicles communicated with the network operating center/server and were charged based on their designated grid charge unit. The total revenue for these 500 vehicles was confirmed in the MongoDB database, and the overall result is illustrated in **Table 5**.

The second scenario in the proposed method is for model year 2030 and is identical to the first scenario. The change point is the percentage of cars in the 500-vehicle sample, which is 50 percent of conventional gasoline cars, 30 percent of hybrid vehicles, and 20 percent of electric vehicles, to represent the forecasted percentage for model year 2030 [41]. The simulation ran for one hour, and the revenue collection was confirmed in the database, as illustrated in **Table 6**. It is assumed that for model year 2030, all vehicles will be charged gasoline tax by the proposed method. Therefore, since electric vehicles are charged based on a grid-based charging system, the collected tax results in a revenue increase of up to 21.8 percent, as illustrated in **Table 6** and **Figure 14**.

Table 5. Shows analyzed parameters in the proposed method for model year 2022.

Vehicle Types	parameters for model year 2022			
	Grid-time unite, Grid/L (5 meter/L)	20% Tax of gasoline price $	Veh types % in 500 Veh Sample	Total Revenue, Vehicle types $
Passenger car	0.00029 * 200	0.25	64.2% = 321	4.65
Hybrid car	0.00029 * 200	0.25	35% = 174	2.523
Electric car	0.00029 * 200	0.25	0.8% = 4	0.058
Total	0.058	0.25	500	7.25

Table 6. Shows analyzed parameters in the proposed method for model year 2030.

Vehicle Types	parameters for model year 2030			
	Grid-time unite, Grid/L (5 meter/L)	20% Tax of gasoline price $	Veh types % in 500 Veh Sample	Total Revenue, Vehicle types $
Passenger car	0.00029 * 200	0.25	50% = 250	3.62
Hybrid car	0.00029 * 200	0.25	30 % = 150	2.175
Electric car	0.00029 * 200	0.25	20% = 100	1.45
Total	0.058	0.25	500	7.25

6.2. Flat Fee Method

The flat-fee method is calculated for 500 vehicles for one kilometer using the formula Equation (1). The fuel price is assumed to be constant at $1.25 for both model years 2022 and 2030. In Equation (1), R represents revenue in dollars, VKMT represents vehicle kilometer traveled; for this study, one kilometer is considered; L/KM represents fuel economy in kilometer per liter; C represents the fuel tax, which is 20%, a combination of 10% local tax revenue and 10% national tax revenue; and N represents the number of vehicles driven in one kilometer.

$$R = \mathrm{VKMT} * (1\mathrm{L/KM}) * C * N \tag{1}$$

In the third scenario for model year 2020, the fuel price is $1.25 per liter and the 20% tax (C) on the fuel price is 0.25. In a 500-vehicle sample, conventional gasoline vehicles, hybrids, and electric vehicles received 64.2 percent, 35 percent, and 0.8 percent, respectively, for model year 2022. The VKMT is one kilometer since we are calculating revenue for one kilometer. Furthermore, fuel economy for conventional gasoline vehicles is 17.2 km/L and hybrids are 20.3 km/L, which is converted to liters/km for model years 2022 [41].

Since, in the current condition, electric vehicles are not paying the gasoline tax, the electricity cost is considered instead of the gasoline tax. The average efficiency of the Nissan Leaf is 164 Watthour/km, which is 0.061 kW per kilometer. The average price of one kilowatt in Japan is $0.19, and we assumed that the electricity tax is also 20%. In a 500-vehicle sample, the BEV percent is considered 0.8 percent to represent the current BEV and PHEV for model year 2022. Based on the above-mentioned parameters, the gasoline tax revenue is calculated using Equation (1) for model year 2022 as demonstrated in **Table 7**.

The fourth scenario is for model year 2030. The fuel price is assumed to be constant and the unit price of (C) is the same as 0.25 as well as the vehicle traveled distance is one kilometer. In a 500-vehicle sample, conventional gasoline vehicles are expected to account for 50%, hybrid vehicles for 30%, and electric vehicles for 20%. Furthermore, the average fuel efficiency for model year 2030 is 25.4 km/L is forecasted, which is converted to L/km as 0.04 liters/km [41].

Table 7. Shows analyzed parameters in the flat-fee method for model year 2022.

Vehicle Types	Parameters for model year 2022			
	Grid-time unite, Grid/L (5 meter/L)	20% Tax of gasoline price $	Veh types % in 500 Veh Sample	Total Revenue, Vehicle types $
Passenger car	0.058	0.25	64.2% = 321	4.65
Hybrid car	0.05	0.25	35% = 174	2.175
Electric car	0.061 kw/km	0.004, Elec price	0.8% = 4	0.001
Total	0.079	0.25	496	6.825

The average efficiency of the Nissan Leaf is assumed to be the same at 164 Wh/km, which is 0.061 kW per km for this study. The average price of one kilowatt is $0.19. Electricity tax is assumed to be 20% in Japan. As of model year 2030, the percentage of BEVs is expected to be 20%. Based on the above parameters, the gasoline tax revenue is calculated using Equation (1) for model year 2030 as illustrated in **Table 8**. As the number of electric vehicles in the global market grows and fuel efficiency improves, revenue will decrease continually.

6.3. Car Ownership Comparison for Grid-Based Charging and Flat-Fee Method

This total cost of ownership is the sum of all the expenditures associated with purchasing and operating a vehicle over a period of time. This cost includes not only the purchase and financing price of the vehicle but also maintenance costs, gasoline costs, insurance, and depreciation costs. Total car ownership can vary substantially across different countries. For this study, to specify the parameters and vehicle characteristics, we considered the annual cost of ownership in Japan.

In this study, the following representative vehicles are considered among all different types of vehicles, such as the Toyota Prius (HEV) for hybrid electric vehicles and the Nissan Leaf Battery Electric (BEV), as well as compared with conventional gasoline vehicles such as the Toyota Corolla for Japan. The typical comparison vehicles were chosen for their significant market share, model size, and representation of different vehicle types. The annual ownership cost for the vehicles mentioned is calculated using the following parameters: annual tax and fee; annual maintenance; insurance; gasoline and electricity costs; and average annual mileage.

The vehicle tax and fee systems have changed over the time period. Therefore, for this study, the total cost of ownership is considered only for the model year 2022. In Japan, three distinct taxes must be paid: an acquisition fee based on the vehicle's Manufacturer Suggested Retail Price; a weight tax every two years; and an annual tax [42]. The annual tax and fee in Japan are paid differently for each type of vehicle, such as an average for conventional gasoline vehicles of $1078, average for hybrid vehicles of $315, and an average for electric vehicles of $315 [43].

Table 8. Shows analyzed parameters in the flat-fee method for model year 2030.

Vehicle Types	Parameters for model year 2030			
	Grid-time unite, Grid/L (5 meter/L)	20% Tax of gasoline price $	Veh types % in 500 Veh Sample	Total Revenue, Vehicle types $
Passenger car	0.058	0.25	50% = 250	3.62
Hybrid car	0.04	0.25	30 % = 150	1.5
Electric car	0.061 kw/km	0.004, Elec price	20% = 100	0.025
Total	0.05	0.25	400	5.145

The average annual maintenance cost for each vehicle type is different for each type of vehicle. Electric vehicles were found to be less expensive due to lower brake wear and fewer moving parts. Annual taxes and fees are $358 per year for traditional gasoline vehicles, $323 for hybrid vehicles, and $276 for electric vehicles, as explained in detail in [43].

In the case of car ownership costs, the annual fuel cost is usually the largest operating cost; therefore, it is important to use representative real-world driving fuel consumption. The average gasoline cost for a conventional gasoline vehicle (corolla) is calculated to be $663. As well, the annual gasoline cost for hybrid vehicles is $562 considered [43].

The insurance is mainly dependent on the vehicle model, condition, insurance company, and other factors. The Prius is classed as an average vehicle for insurance purposes [44].

Therefore, the average comprehensive insurance cover is considered to adequately represent insurance costs for all vehicle types. Therefore, for this study, we assumed full insurance at an average cost of $1512 in 2022 for a Prius vehicle to adequately represent insurance costs for all vehicle types [45].

The average annual travel distance of LDVs is 9120.3 km [46]. The fuel price and the fuel economy for each type of vehicle are used to calculate the gasoline cost. The average fuel economy for conventional gasoline vehicles is 17.2 km per liter, while hybrid vehicles average 20.3 km/L for model year 2022, and electric vehicles are considered the same as hybrid vehicles for this study. In addition, for model year 2030, conventional gasoline vehicles have an average fuel economy of 20.1 km/L, hybrid vehicles have an average of 25.4 km/L, and electric vehicles are considered the same as hybrid vehicles. For models 2022-2030, the fuel price is assumed to be constant for both model years at $1.25 per liter.

Since BEV vehicles do not use gasoline, the electricity cost is considered for the Nissan Leaf. The average annual electricity cost is dependent on the increased efficiency of the electric drive power train during urban or rural driving. Annual fuel costs are usually cheaper for BEVs and PHEVs depending on the percentage of driving in fully electric mode. The average efficiency of the Nissan Leaf is 164 Wh/km, and it can travel 6.1 kilometers at one kilowatt [47]. As well, the average annual travel distance is considered the same as a hybrid vehicle, which is 9120.3 km, and the average price of one kilowatt in Japan is $0.19. Based on these parameters, the average annual cost of electricity is $284.

The annual gasoline tax (20%) is calculated for each type of vehicle based on the average annual travel distance of LDVs of 9120 km, the 20% fuel price of $1.25, and the fuel economy for each vehicle type for the current flat-fee method.

The annual ownership cost is calculated for conventional gasoline, hybrid, and battery electric vehicles and compared for both model years 2022 and 2030 as illustrated in Figure 12 and Figure 13.

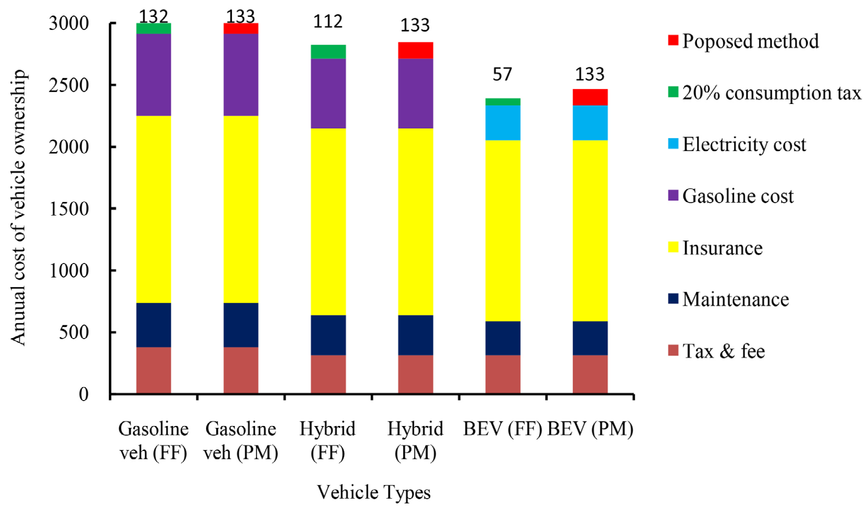

Figure 12. Annual usage cost of ownership in currant flat-fee and proposed method (PM) model year 2022.

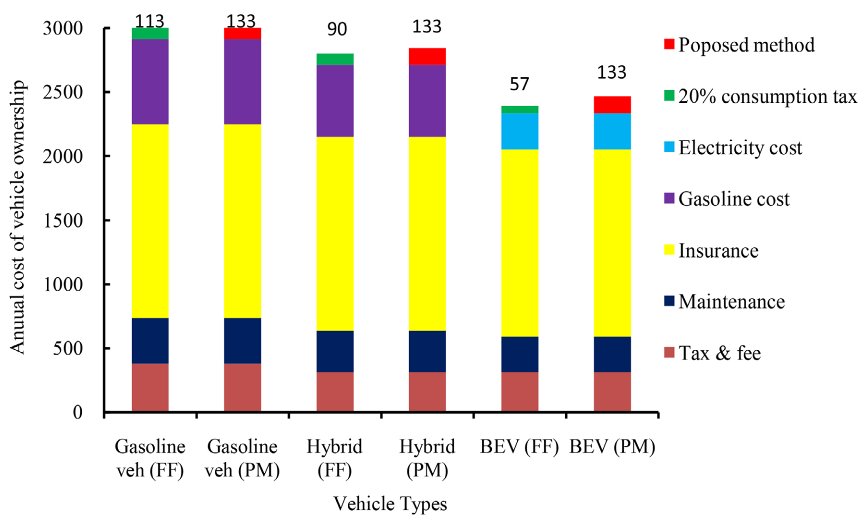

Figure 13. Annual usage cost of ownership in currant flat-fee (FF) and proposed method (PM) model year 2030.

7. Result and Discussion

A software platform has been developed based on a grid-based charging system as an alternative for collecting gasoline tax from zero-emission vehicles. In the new method, spatio-temporal sections are created as equal grids of space and time for the road. All vehicles can reserve the grid, route, and travel based on the reservation role and charge dynamically upon arrival at their destination. This provides maximum auditability to the user for each trip's information and tax charges. The reservation role will improve traffic management as well as improve dynamic maps based on real-time information collection. A designated tax fee is assigned per grid (5 meters/second) to the various types of vehicles to utilize as minimum travel distance tax charges. The designated tax charge unit is created for each type of vehicle based on its fuel consumption; it could be developed for any type of vehicle and integrated into the platform for numerous types of vehicles. The platform does not save any trip GPS data until the user pays the taxes and collects the minimum information to provide privacy to users. The new method is based on a reservation system that will provide assistance to emergency vehicles in traveling to their destinations on time. The revenue could be generated by collecting fees from emergency vehicles as well, which would increase the total revenue.

The load test was conducted to measure communication time requests and responses. The maximum response time for processing each vehicle was less than 48 milliseconds. However, when the number of requests increased, the average value of the response time decreased, as shown in **Table 3**. The main reason is that in the proposed method, the asynchronous processing method is implemented with non-blocking I/O. Whenever the number of requests increases, it simultaneously increases the processing threads, which reduces the response times. However, when the number of processed requests reached 50, inconsistencies occurred twice in the data storage. Therefore, when operating in a real environment, inconsistencies could be avoided by determining the number of requests to be handled for each thread on a server.

As shown in **Figure 6** and **Figure 9**, the proposed method's performance was successfully tested by checking the grid reservations and collecting the gasoline taxes using the spatio-temporal grid-charging method. We confirmed that if 100 vehicles submit requests, the server can reserve grids, compute the travel distance, impose tax charges, and send invoices to the billing center for 100 vehicles. Furthermore, since we created a one-kilometer road environment in VISSIM, to assure accuracy, the distance traveled and tax charges for each vehicle were confirmed in the server database as 1000 meters and 0.0125 dollars.

We repeated the same procedure to validate the performance of different vehicle inputs and found that the proposed method functioned accurately. To summarize, we confirmed that the system can safely collect gasoline tax revenue for all types of vehicles based on a micro-road-pricing method without errors or data package losses for distance traveled. Each time the vehicle travels, the vehicle user could audit in detail his travel and tax information. To protect user privacy, only the vehicle ID, travel distance, tax charges, and invoice number related information are disclosed to the billing center.

We evaluate and compare the gasoline tax of a 500-vehicle sample for one kilometer as well as the annual ownership cost for both the proposed and current flat-fee methods. Table 5 and Table 6 demonstrate the grid-based charging system results, which show a 5.7 percent revenue increase for model year 2022 as well as 21.8 percent for model year 2030, as shown in Figure 14. Table 7 and Table 8 illustrate the gasoline tax revenue of 500 vehicle samples in one kilometer. The result shows that since the electric vehicles are not paying the gasoline tax as well as the hybrid vehicles are paying less tax, the total revenue decreased compared to model years 2022 and 2030.

The proposed software platform is capable of taking taxes from any type of vehicle based on its fuel consumption. We considered only the abovementioned types of vehicles to compare them with conventional gasoline tax collection methods such as the flat fee method. For this study, the grid-based charge fee is considered to be constant, and it is converted based on conventional gasoline vehicle fuel consumption. which applies to hybrids and BEVs as well. Thus, it will bring equity in road tax for all types of vehicles that are using the road, as well as increase the revenue per kilometer.

Furthermore, to better understand the tax burden for each type of vehicle for both methods, we investigate how the annual cost of ownership changes for each type of vehicle for both methods. We found that in model year 2022 the annual gasoline tax differences for conventional vehicles and hybrid vehicles were almost the same, a BEV $76 increase utilizing the proposed method as illustrated

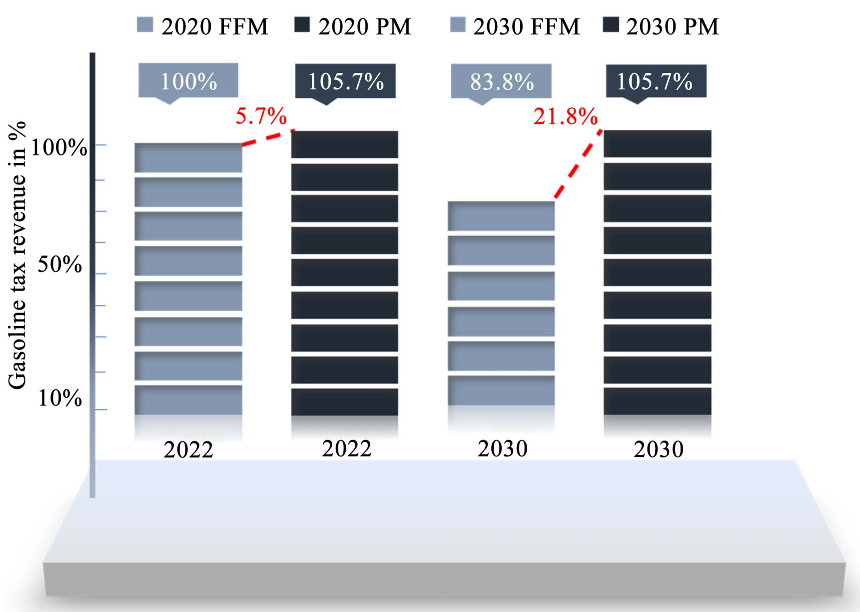

Figure 14. The comparison of total tax revenue for the proposed and flat-fee methods in model years 2022 and 2030.

in **Figure 12**. Furthermore, using the proposed method, the annual gasoline tax differences for conventional vehicles are \$20, hybrid vehicles are \$43, and BEVs are \$76 in model year 2030, as illustrated in **Figure 13**. Since in the proposed method (PM), grid-based charging units are considered constant for conventional, hybrid, and BEV vehicles in both model years 2022 and 2030. Thus, the gasoline tax revenue will increase by 5.7% and 21.8% in 2020 and 2030, respectively, over that gained by the flat fee method (FFM).

8. Conclusions

In this paper, a novel distance-based gasoline tax charging system as an alternative method to replace the current flat-fee method for collecting gasoline tax is proposed. We used the vehicle-driving information through communication methods installed in connected automated vehicles to develop a system to collect gasoline tax. With a dynamic map platform, we created spatio-temporal sections by dividing space-time into equal grids and assigning designated tax charges. The result of our performance evaluation shows that the proposed method adequately reserved grids and accurately collected gasoline taxes based on spatio-temporal grids with minimum data package loss.

We tested and validated that our proposed method accurately generates revenue from all types of vehicles. Each time the vehicle travels, the vehicle user could audit in detail his travel and tax information to maintain privacy. The load test result reveals that the response time was less than 48 milliseconds for communication. The total gasoline tax revenue is supposed to increase by 5.7% and 21.8% in 2020 and 2030, respectively, over that gained by the flat fee method (FFM).

Furthermore, the annual ownership cost difference between the proposed and flat-fee methods is not high. Therefore, the proposed method is capable of providing sustainability and guaranteeing long-term alternative gasoline tax revenue. Since the proposed method is implemented based on reservation role, routes can be reserved in a time frame based on traffic demands with a pricing-based control charging system over traffic density, which will reduce and manage traffic congestion as well as increase revenue for road usage. For the future work, since the new method is based on a reservation system that will provide assistance to emergency vehicles in traveling to their destinations on time. The revenue could be generated by collecting tax fees from emergency vehicles as well, which would increase the total revenue.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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