Incentive mechanism for collective coordination in an urban intelligent transportation system using G-networks

Huibo Bi, Erol Gelenbe, Life Fellow, IEEE, and Yanyan Chen

Abstract—**Although the abilities of human traffic participants in decision-making and interacting with transportation infrastructures have been greatly amplified by the powerful portable devices and efficient human-machine interfaces, the intelligence of traffic participants (e.g. drivers and pedestrians), as well as the production of possible pro-social behaviours such as helpfulness and sense of duty, have been excluded in the previous ITS. As a result, the robustness of an ITS cannot be ensured due to the high likelihood that participants do not follow the instructions. Moreover, unnecessary efforts have been dedicated to the use of Artificial Intelligence, while in fact many tasks can be easily accomplished by road users in the system via using human intelligence. Hence, in this paper, we propose a reward mechanism to integrate the human intelligence of involving road users into a large-scale transportation system to improve the effectiveness and robustness of the system by introducing a transportation-related task publishing system with the assistance of a queueing network model. The experimental results show that the use of the reward mechanism can significantly improve the performance of the transportation system in terms of average travel time of vehicles and the average response time to various tasks.**

Index Terms—**Intelligent Transportation Systems, Reward Mechanism, Traffic Management, Intelligence Augmentation, G-networks.**

I. Introduction

The advancement of artificial intelligence in the recent decades has revolutionised the methodology and technique in urban traffic control, and has unveiled the emergence of various intelligent transportation systems. However, as a typical category of cyber-physical systems, the intelligence of participants has been, to some extend, excluded in the previous intelligent transportation systems, and the positive intrinsic and extrinsic characteristics of drivers, such as helpfulness and sense of duty, which have the potential to generate efficient cooperative collective behaviours, have not been motivated and considered as influence factors. Hence, in this paper, we propose a reward mechanism to encourage human intelligence augmented cooperative behaviours via rewarding credits to stimulate road users to carry out various types of tasks. The credits, which are expected to be fully exchangeable with currency, can also be used in exchange for better quality of services in the system or other authorised benefits. The transportation system is modelled with a queueing network based model to capture the dynamics of traffic flow under the effects of the reward mechanism. A gradient descent optimisation algorithm is employed to increase the social benefits and improve the traffic efficiency by solving the desired credit values via optimising the probabilistic choices of linked road segments at each task-publishing intersection with respect to historical observations on routine traffic. The remainder of the paper is organised as follows: we first review the related work in Section II, followed by the system model in Section III, which is composed of problem formulation in III-A, the system approximation model in III-B and the cost-benefit goal function in III-D. The simulation assumptions and results are introduced in Section IV. Finally, we draw conclusions in Section V.

II. Related Work

A. Human-augmented Computing In Transportation

In the research field of transportation, human-augmented computing has mostly been used in collectively solving transportation related problems in a "crowdsourcing" manner, such as "crowd delivery" and "crowd sensing". For instance, owing to the inaccurate or less detailed near-destination navigation provided by the popular digital map services, the research in [1] presents a "social navigation" algorithm to plan the last mile routes for drivers by connecting the top-ranked landmarks scored by experienced local drivers; in addition, to fight against the vulnerability of crowdsourcing systems to malicious attacks, a trajectory estimation approach is employed for location authentication by inferring the future possible locations of users, the users whose GPS points are frequently mismatched with the predictions will be considered as attackers and discarded. Similarly, the study in [2] developed a human augmented route recommendation system to provide routes for mobile phone users with the aid of experienced users; to facilitate crowd to use the system, a user-friendly human machine interface is designed to show candidate routes on a digital map where users can select by a single click; moreover, users are given various reward points in terms of their recommendation frequency and quality, the reward points can be used in exchange for a new recommendation request. On the other hand, the research in [3] has a special focus on the malicious bidding and free-riding behaviours (users are given rewards but pay no effect in executing sensing tasks) in crowd sensing; a three-step incentive mechanism is proposed to ensure the fairness of rewards and high quality of the sensed data during a crowd sensing process via service provider selection, service provider payment determination and sensory data quality evaluation; the incentive mechanism is mimicked and verified with a combination of a reverse auction and a Vickrey auction model.

However, to the best of our knowledge, although several research has integrated the use of human intelligence into ITS by taking advantage of the advanced visual perception and decision-making ability of human being. No related research has presented a comprehensive incentive based system framework to motivate participants to take part in the operations and decision-making of a transportation system, and analyse the influence of the introduction of the incentive mechanism.

B. Reward or Incentive Mechanisms In Transportation

Nowadays, although various point-based or badge-based reward systems [4] have been implemented to motivate participants or evoke perceptions of enjoyment in crowdsourcing systems such as crowdsourcing games [5] or file caching in delay tolerant networks [6], and the performance of these systems is proven to exceed the non-reward counterparts, only a few studies have been dedicated to the field of ITS. The use of reward mechanisms in the existing research of ITS is mostly reported in the crowdsourcing based transportation systems as a approach to motivate the share of experience and courses of cooperative action among users such as route-recommending and accident-monitoring. For example, the research in [7] presents a Blockchain based announcement network, namely "CreditCoin", to motivate users to forward transportation information in a vehicular announcement network; in this system, each user is assigned with a credits account which contains reputation points; users can gain reputation points by relaying announcements or making an announcement such as reporting an accident. The work in [8] designs a traffic incident report system to identify various road situations by leveraging the reports from passing-by drivers; a monetary reward mechanism is introduced to improve the reliability and willingness of drivers to provide truthful reports; the experimental results show increased inference accuracy rates with the aid of a modified weighted majority voting and Bayesian inference approaches. Although several studies [9], [10] have proposed the use of credits to optimise the travel mode and pattern of users, most of them are investigated from an analytical point of view to evaluate the effects of the credit schemes rather than an online system implementation aspect. For instance, the research in [11] discusses possible tradable credit distribution and charging schemes for homogeneous users to reduce traffic demand; the credits are presumed to be issued and distributed to eligible users by the government and can be traded among users; users are charged with a specific amount of credits in terms of the used road segment; the research shows that an user equilibrium can always be reached under either fixed or elastic traffic demand.

In the research field of transportation, a popular trending that is similar to the use of incentive mechanisms is employing various rationing and pricing strategies to regulate the behaviours of participants. For instance, the study in [12] discusses the robustness of two pricing strategies used to direct traffic away from congested areas; the two pricing strategies are fixed tolling which simply charges users of each link with a fixed price and marginal-cost tolling which assigns each link with a flow-varying toll; the two strategies are evaluated under various scenarios including network structure changing, traffic rate changing and traffic demand changing; the simulation results show that the marginal-cost tolling strategy is much more robust than fixed tolling, but still lack robustness to heterogeneous users with different price sensitivity. The research in [13] analyses and compares the effectiveness of existing or potential traffic demand management policies, including rationing policies and road pricing policies; rationing policies such as vehicle ownership rationing and vehicle usage rationing are jointly analysed with the impact of road pricing policies; the numerical results show that (1) the vehicle usage rationing strategies always causes user welfare losses from a long-term perspective; (2) the road pricing strategy always generates more social welfare than rationing policies. In [14] a dynamic pricing system is presented to optimise the "Last-Mile" travel service by offering different prices for different types of passengers such as aged people, children or students; the last-mile service process is modelled as a batch arrival, batch service, multi-server queueing model and the optimal prices for passengers are determined by a constrained nonlinear optimization model. Similarly, the work in [15] proposes a dynamic pricing policy to mitigate congestion and offer reliable travel time for road users on managed lanes with multiple entrances and exits; a deterministic Markov decision model is employed to solve the optimal toll rate with the value function approximation approach; a lane choice model is proposed to choose routes for road users at each diverge point with the consideration of all possible routes; the experimental results show that the proposed model and related algorithm is efficient at discovering the optimal tolls.

However, although various rationing or pricing strategies have been proposed to optimise the traffic demands or traffic flows, most research has limited to pure traffic management rather than system management. In addition, the fairness of rationing and pricing strategies could cause disputes when charging heterogenous users with different tolls.

III. System Model

To introduce and motivate human intelligence and positive collective behaviours into current intelligent transportation systems, we design a novel reward mechanism that can improve social benefits and traffic efficiency by establishing a traffic task publishing system. In this section, we first describe and formulate the problem, then propose a comprehensive urban traffic network model to describe and capture the traffic dynamics under the influence of the reward mechanism. Finally, we use a optimisation model to calculate the desired credit for each task.

A. Problem Formulation

As a type of cyber-physical systems, state-of-the-art ITS commonly rely on heuristic algorithms to provide assistance to participants, yet to a great extent, ignore the positive and negative influences of participants inside the system. For example, participants may benefit the performance and efficiency of the system by conducting coordinated collective behaviours such as monitoring and reporting unattended accidents, avoiding certain types of vehicles such as bicycles or coaches, and hitchhiking. On the other hand, participants may not follow or obey the instructions of the ITS, and as a result, may significantly reduce the performance of the ITS.

In this paper, we propose a reward mechanism to encourage the participants to conduct cooperative tasks by introducing a task publishing system. The cooperative tasks are categorised into 3 types: low level sensing tasks, high level cooperative tasks and simple route diversion tasks. For low level sensing tasks, since it is expensive and impossible to deploy sufficient sensors to cover the whole area of a large-scale urban traffic system, it would be helpful if road users are driven to monitor and report the unattended accidents or other dangerous behaviours. For high level cooperative tasks, it is obvious that the performance of a ITS will be increased if road users are prone to coordinate with others, such as avoiding specific vehicles or choosing a less congested route. In addition, road users are also encouraged to conduct prosocial behaviours to further optimise the performance of the system by allowing hitchhiking, pulling over at peak hours, etc. For the simple route diversion tasks, they are generated by the task-publishing system when there are not sufficient tasks to achieve the optimal route flow ratio. In the proposed mechanism, we reward different tasks with dynamic reward points to regulate collective behaviours and optimise the performance of the system with respect to diverse traffic situations and demands. Participants can sell their credits in exchange of money or to gain other authorised benefits.

B. G-network based System Approximation Model

Since our reward distribution framework requires certain traffic information to compute desired credit values for users, we assume an ITS system with sensing and computing facilities is pre-deployed in the targeted traffic network. The traffic network of the designated area is simplified as a directed graph consisting of nodes and edges. Nodes are intersections where vehicles can queue up and wait for the traffic signal progression, as well as receive credit scoring tasks from the reward distribution framework. Edges are road segments that link the intersections. Each intersection is considered as a queueing system of one single server with Poisson arrival users and exponentially distributed service time, and therefore the whole network can be modelled as a queueing network. The schematic diagram of a simplified road network, depicting the relations among joint intersections and the task publishing system, is shown in Figure 1. When a user approaches a task publishing intersection, rather than choosing the next edge based on each civilian's own interests or the GPS instruction, certain credit scoring tasks can be sent to the users and incentivise users to choose a route to conduct cooperative tasks. To this end, we employ a G-network model to formulate the system dynamics and increase the likelihood for civilians to conduct cooperative tasks by providing appropriate credits for probabilistic choices of all available cooperative tasks to maximise social benefits and traffic efficiency.

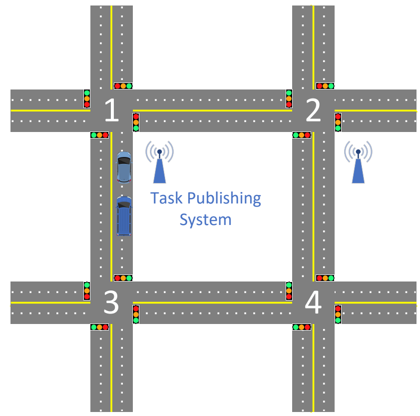

Fig. 1. The schematic diagram of several intersections and the task publishing system within the road network.

G-networks [16] are a class of queueing network models that can describe real-world processes and practical scenarios with basic entities —positive customers, and additional control factors including negative customers [17], removals [18], triggers [18] and resets [19]. G-networks have been used in a wide range of applications, including describing the workload in computer systems [20], [21], realising energy efficiency in packet networks [22], as well as modelling energy systems [23], [24], populations of biological agents [25] and gene regulatory networks [26]. One useful property of the G-networks is the existence of a product form solution (PFS) [18], where the joint equilibrium distribution of the number of positive customers in the network can be derived.

The exact model we use to capture the dynamics of a routine traffic process is based on [18], and has only positive customers and triggers representing vehicles and re-routing decisions affected by credit scoring tasks, respectively. The positive customers (vehicles) that have just started to move from the stationary state will enter the network by joining their nearest intersections, and this "external" arrival of vehicles to n_i occurs at an average rate of Λ_{n_i}. The average service rate of vehicles at intersection n_i is denoted by r_{n_i} which depends on the physical characteristics of the node including the size and number of intersecting roads, as well as potential credit scoring tasks that may cost certain time to accept and handle. A vehicle which is leaving intersection n_i will either head towards another connected intersection n_j with probability P_{n_i,n_j} or leave the network (reach the destination or pull over at the side of the road) with probability d_{n_i}. If we assume there are N intersections in the network, then the routing choices of vehicles yield:

$$d_{n_i} + \sum_{j=1}^{N} P_{n_i,n_j} = 1 \qquad (1)$$

Meanwhile, the road users may respond to reward gaining tasks, which are periodically published by the remote control center, to conduct cooperative tasks. The tasks are generated based on the requests of road users or the transportation system. The tasks reach users at an intersection n_i at average rate $\lambda^-_{n_i}$, instructing the surrounding vehicles to conduct certain cooperative tasks by moving to intersection n_j with probability Q_{n_i,n_j}, where $\sum_{j=1}^{N} Q_{n_i,n_j} = 1$. This probability, which is associated with and affected by the potential credit, is a key parameter to be optimised in our system, as previous research [22] has indicated that it can significantly affect the performance.

With the aforementioned assumptions, the steady-state probability that an intersection n_i has one or more vehicles is given by [18]:

$$q_{n_i} = \frac{\lambda^+_{n_i}}{r_{n_i} + \lambda^-_{n_i}} \tag{2}$$

where $\lambda^+_{n_i}$ is the total average arrival rate of vehicles to intersection n_i, including vehicles that were previously parked or at other intersections:

$$\lambda^+_{n_i} = \Lambda_{n_i} + \sum_{j=1}^{N} q_{n_j}[r_{n_j} P_{n_j,n_i} + \lambda^-_{n_j} Q_{n_j,n_i}] \tag{3}$$

Notice that the quantities q_{n_i} are coupled, and therefore (2) is a nonlinear equation that can be solved numerically. Term r_{n_i} is the average service rate at intersection n_i and it is the inverse of the average service time. The service time is defined as the time cost for a vehicle to traverse from one intersection to another, it is the summation of the time cost at the intersection and the time cost on the link.

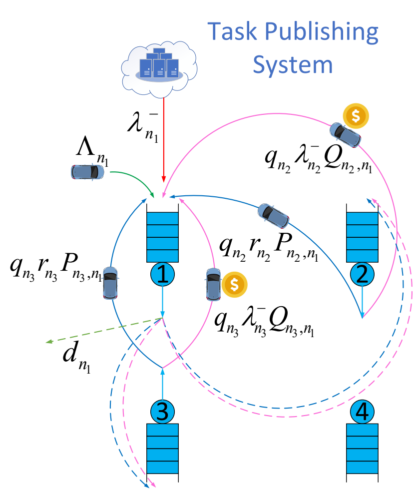

Fig. 2. The G-network diagram of the intersection 1 shown in Figure 1.

Based on the aforementioned PFS property, let $K_{n_i}(t)$ denotes the number of vehicles at time t in intersection n_i, then the joint equilibrium distribution of the number of vehicles in the network has a product form and is given by:

$$\Pr(K_{n_i} = k_i,\ i = 1, 2, \ldots, N) = \prod_{i=1}^{N} q_{n_i}^{k_i}(1 - q_{n_i}) \tag{4}$$

With this product form, we can readily analyse the current state of the system, especially the on-going distribution of vehicles within the system, by calculating q_{n_i} at each intersection.

C. Point-based Reward Value Determination

The credits, which are the reward points used to incentivise the road users to conduct cooperative tasks during the transportation process, are modelled as the offsets between the "original status" of civilians to conduct cooperative tasks and the "optimised status" of civilians to conduct cooperative tasks from the system performance point of view. The "original status" of civilians is defined as the number of "willing-to-help" and probabilistic choices of civilians for various cooperative tasks without introducing the reward mechanism. On the other hand, the "optimised status" is considered as the potential number of "willing-to-help" civilians under the influence of the proposed reward mechanism and optimised probabilistic choices of civilians who would like to offer help in the optimal case with respect to the overall system performance such as average traffic delay or fuel utilisation.

To formulate this point-based reward mechanism clearly, firstly, we focus on a single intersection to investigate the relations among factors of interest, which can be extended and applied to a whole urban network; secondly, we build an optimisation model for the point-based reward value determination problem and solve it with a nonlinear programming approach.

Consider an intersection n_i that is directly linked with other m intersections $\{n_1, n_2, \cdots, n_m\}$, where n_j refers to the intersection with identifier j. The set of credit scoring tasks that are published at each intersection is denoted by $B = \{b_1, b_2, \cdots, b_K\}$, where b_k refers to the task type with identifier k, term K represents the number of task types. Let term N_{n_i} denotes the total number of road users who arrive at intersection n_i. Term $T^{b_k}_{n_i}$ represents the transfer rate between the total number of civilians who arrive at the intersection and the total number of civilians who are willing to conduct credit scoring tasks of type b_k at the intersection. In other words, it represents the percentage of road users that conducts tasks of type b_k. Term $P^{b_k}_{n_i,n_j}$ denotes the percentage of tasks of type b_k conducted by moving towards intersection n_j. In our treatment, $P^{b_k}_{n_i,n_j}$ is set to be directly proportional to the number of published tasks that can be conducted by moving towards intersection n_j. Hence, Q_{n_i,n_j}, which is aforementioned in subsection III-B as the probability for a vehicle to conduct certain credit scoring tasks by moving towards intersection n_j, can be expressed as:

$$Q_{n_i,n_j} = \frac{\sum_{k=1}^{K} N_{n_i} T_{n_i}^{b_k} P_{n_i,n_j}^{b_k}}{N_{n_i}} = \sum_{k=1}^{K} T_{n_i}^{b_k} P_{n_i,n_j}^{b_k} \quad (5)$$

Hence, we build the relation between variables Q_{n_i,n_j} and $T_{n_i}^{b_k}$. Therefore, $T_{n_i}^{b_k}$ can be solved since Q_{n_i,n_j} can be determined by gradient descent optimisation. Term $P_{n_i,n_j}^{b_k}$ can be obtained by on-site observation or set as empirical values based on the following equation:

$$P_{n_i,n_j}^{b_k} = \frac{I_{n_i,n_j}^{b_k}}{\sum_{c=1}^{m} I_{n_i,n_c}^{b_k}} \quad (6)$$

where term $I_{n_i,n_j}^{b_k}$ represents the number of published tasks that can be conducted by moving towards intersection n_j. Term m denotes the number of intersections that are directly connected with intersection n_i. Term m stands for the number of intersections that links to intersection n_j.

The next step after determining $T_{n_i}^{b_k}$ is to resolve $\widehat{R}_{n_i}^{b_k}$, which represents the point-based reward value for task type b_k at intersection n_i. During the operation of the reward-scoring mechanism, certain reward points $\widehat{R}_{n_i}$, which are directly proportional to transfer rate $T_{n_i}^{b_k}$ at intersection n_i, are assigned to each intersection n_i to encourage civilians to offer help. This is reasonable as it implies that with the increase of the reward points, people are more and more likely to take part in. Form the task-publishing system point of view, we aim to minimise the cost of reward points to achieve the traffic management goal. The formulation of the problem is shown as follows:

$$\begin{aligned}
&\min \sum_{k=1}^{K} \widehat{N}_{n_i}^{b_k} \widehat{R}_{n_i}^{b_k} \\
&\text{subject to:} \\
&\sum_{k=1}^{K} T_{n_i}^{b_k} P_{n_i,n_j}^{b_k} = Q_{n_i,n_j} \quad \forall\, Q_{n_i,n_j} \\
&\widehat{N}_{n_i}^{b_k} = T_{n_i}^{b_k} N_{n_i} \\
&\widehat{R}_{n_i}^{b_k} = \alpha_{b_k} T_{n_i}^{b_k} \\
&\widehat{N}_{n_i}^{b_k} \le \sum_{c=1}^{m} I_{n_i,n_c}^{b_k} \\
&\widehat{R}_{n_i}^{b_k} \ge 0
\end{aligned} \quad (7)$$

where term $\widehat{N}_{n_i}^{b_k}$ denotes the number of accepted tasks of type b_k, and term α_{b_k} denotes the relation between reward points $\widehat{R}_{n_i}^{b_k}$ and task transfer rate $T_{n_i}^{b_k}$. The relation between $\widehat{R}_{n_i}^{b_k}$ and $T_{n_i}^{b_k}$ is obtained by a questionnaire survey. In our treatment, for the sensing tasks b_1, cooperative tasks b_2, and simple route diversion tasks b_3, term α_{b_1}, α_{b_2} and α_{b_3} are set to 200, 166.7 and 71.4, respectively. It is also worthy to note that, in order to fulfill the above restrictions, the task-publishing system will have to release some simple route diversion task if there are not sufficient tasks to achieve the optimal route flow ratio Q_{n_i,n_j}. From the implementation aspect, solutions can be obtained by using "CVXPY", which is a Python-based modeling package for convex optimization problems.

D. Cost-benefit Estimation Model

In this section, we mainly introduce the cost-benefit estimation model, or in other words, the goal function (objective function), to calculate the optimal route flow ratio for users to conduct credit scoring tasks at each intersection. The performance we aim to optimise are twofold: traffic efficiency and social benefits. The traffic efficiency is defined as the total delay for a vehicle to experience in the network. The social benefits are simplified as the cost for a task request to receive respond inside the network.

For a vehicle, the total delay in the urban network includes delays at both intersections and road segments, and depends on the congestion level. Since we have modelled the road network as a queueing network, the average number of vehicles at a queue can be derived directly from (4) yielding:

$$N_{n_i} = \frac{q_{n_i}}{1 - q_{n_i}} \quad (8)$$

Using Little's formula, the average traversal times are given by:

$$D_{n_i} = \frac{N_{n_i}}{\lambda_{n_i}^{+}} \quad (9)$$

while the total average delay experienced by a vehicle in the network is:

$$D_t = \frac{\sum_{i=1}^{N} N_{n_i}}{\sum_{i=1}^{N} \Lambda_{n_i}} \quad (10)$$

where the numerator is the total average number of vehicles in the network, and denominator is the total rate at which vehicles join the network.

On the other hand, the cost for a task request to receive assistance in the network is affected by its occurrence position, type of the task request, arrival rate of this type of task request, number of vehicles at the intersection, percentage of vehicles that is willing to conduct this type of task:

$$P_s = \sum_{i=1}^{N} \sum_{k=1}^{K} \frac{Pr_{n_i}^{b_k} q_{n_i} T_{n_i}^{b_k}}{1 - q_{n_i}} \quad (11)$$

where $Pr_{n_i}^{b_k}$ is the probability for a task request of type b_k to appear at the intersection n_i, which are defined in (12).

$$Pr_{n_i}^{b_k} = \frac{\lambda_{n_i}^{b_k}}{\sum_{i=1}^{N} \sum_{k=1}^{K} \lambda_{n_i}^{b_k}} \quad (12)$$

where term $\lambda_{n_i}^{b_k}$ is the arrival rate for a request of type b_k to reach the network from node n_i, which can be calculated by statistical approaches.

To achieve social benefits with a acceptable network latency, we combine the two metrics above and the goal function can be expressed as:

$$G_c = D_t + \frac{\epsilon}{P_s} \tag{13}$$

where ϵ is a constant that coordinates the relative importance between the traffic delay and social benefits. In our case, ϵ is set to 20. The goal function can be solved by using gradient descent optimisation.

IV. Simulations and Results

We employ a Python based simulation tool, namely the smart environment simulator (SES), to evaluate the performance of our proposed reward mechanism. The SES works as a client to dynamically interact with the open-source simulation platform "Simulation of Urban MObility" (SUMO) [27], which is a microscopic and continuous road traffic simulator as shown in Figure 3. We utilise a 3-days period (2015/08/13 - 2015/08/15) realistic vehicle trip data collected in Beijing City as the input of the SES. Each day is divided into 12 consecutive 2-hour periods to accelerate the experiments by conducting multiply simulations in a parallel manner.

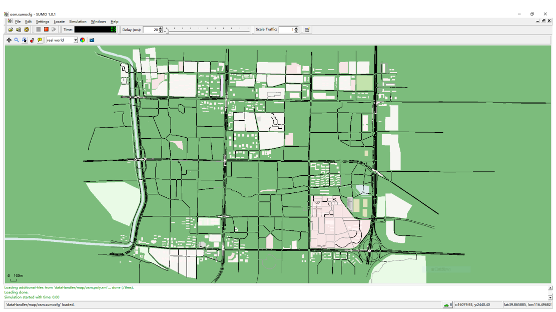

Fig. 3. The graphical user interface of the SUMO-based simulator.

As a preliminary step of the experiments, the raw vehicle trip data are pre-processed in the following 3 steps: first, the vehicles that traversed the designated area are extracted from the raw data; second, the GPS traces of the trips are transformed into the X,Y-coordinates in the SUMO platform and then are linked into integrated routes; third, the processed routes as well as the origin, destination, and the start time of the trips are added into the event engine of the SES in chronological order. When the simulation starts, the trips will be replayed unless a vehicle accepting a re-routing command.

In the experiments, we use 2 scenarios to validate the effectiveness of the proposed mechanism. The first scenario, which is used for the comparison propose, is the original courses of action of the vehicles in the road network. The second scenario is the courses of action of the vehicles under the impact of the proposed reward mechanism. In the experiments, we assume that 3 types of tasks are being published, sensing tasks, cooperative tasks and simple route diversion tasks. The sensing tasks are generated at the rate of 5 tasks per hour at each task publishing intersection to direct road users to inspect a certain road segment for possible accidents or other malicious behaviours. The cooperative tasks are generated in an on-demand manner at each task publishing intersection to encourage road users to choose less congested routes when congestion occurs. The simple route diversion tasks are also produced in an on-demand manner at each task publishing intersection to encourage road users to fulfil the optimal flow ratio at the intersection. Associating with the optimisation goals, the average travel time, the average response time of reward-scoring tasks are selected as the performance metrics of the experiments.

As can be seen in Figure 4 to Figure 6, the average travel time of vehicles decreases remarkably with the use of the reward mechanism. This is mainly because the reward mechanism encourages the vehicles to choose alternative paths to destinations and avoid the congested original paths. Meanwhile, to finish the reward-scoring tasks, the vehicles are naturally more distributed in the network and are likely to increase the occupancy rates of less popular routes. This can be also proved by the Figure 7 and Figure 8, which show the average number of traversed vehicles for each edge in the network during the 2-hours periods. As it is clearly shown, the use of the reward mechanism can efficiently balance the average visiting times of among all edges. The visiting times of the most visited edge is reduced from 496 to 410.

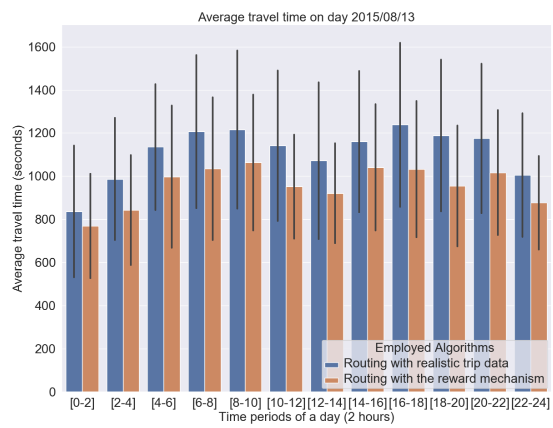

Fig. 4. The average travel time of vehicles in 2-hour periods during 2015/08/13.

On the other hand, the average response time for a score-rewarding task to be accepted in the network is shown in Figure 9. It is affected by the number of vehicles at a task-publishing intersection, the type of the task and the reward value of the task. As it is shown in the figure, most of time periods of a day (from 6 am to 24 pm), the average response time of a task is less than 500 seconds. However, the average response time exceeds 500 seconds during 0 am to 6 am. This is mainly because during wee hours there are not sufficient vehicles to conduct tasks. It is also worth noting that day 2015/08/15 possesses the lowest average response time of a task among the three days. This is because it has the largest average amount of vehicles in the targeted area, and therefore has more candidates to conduct tasks. Similarly, day

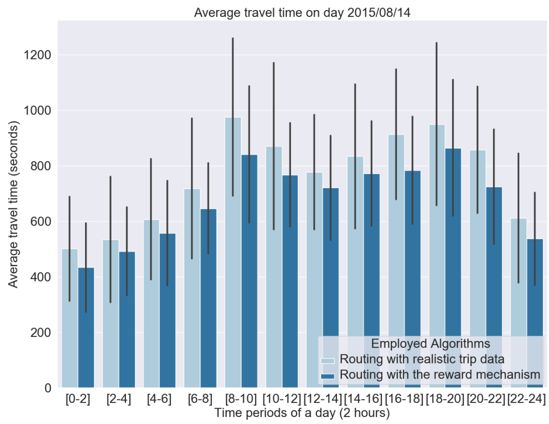

Fig. 5. The average travel time of vehicles in 2-hour periods during 2015/08/14.

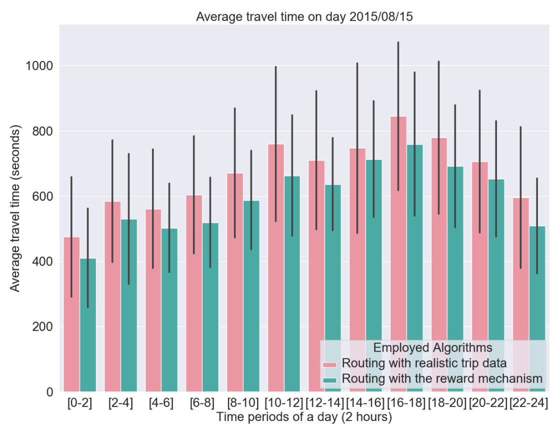

Fig. 6. The average travel time of vehicles in 2-hour periods during 2015/08/15.

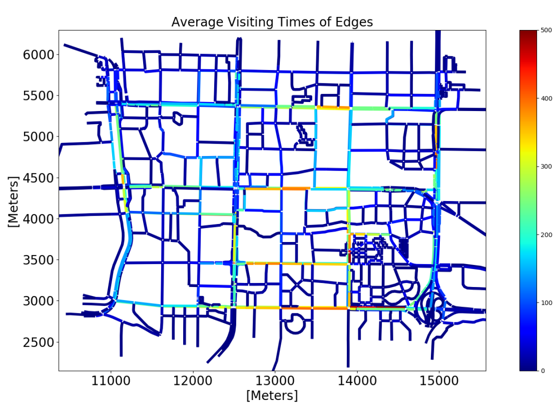

Fig. 7. The average visiting times of each edge in 2-hour periods for routing with realistic trip data.

2015/08/13 possesses the highest average response time due to the fact that least vehicles traversed the area during the day.

The reward points cost by the task publishing system are shown in Figure 10. The pre-set exchange ratio between RENMINBI and the reward point is 1:1. As can be seen clearly in the figure, day 2015/08/13 consumes the lowest

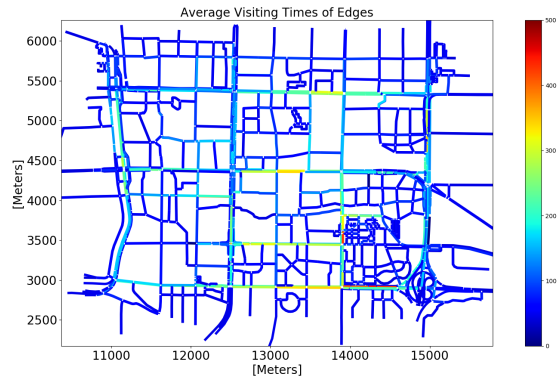

Fig. 8. The average visiting times of each edge in 2-hour periods for routing with the reward mechanism.

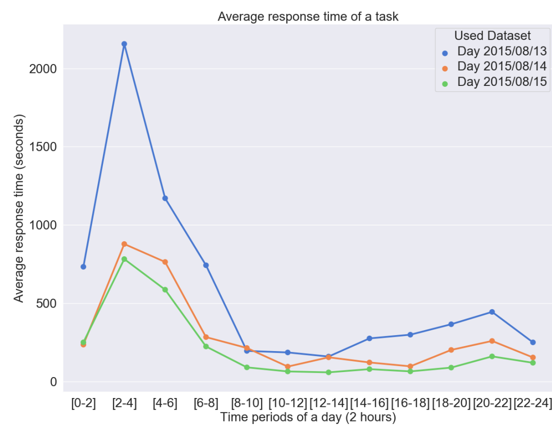

Fig. 9. The average response time of a task in 2-hour periods for the task publishing system.

reward points while day 2015/08/15 consumes the highest reward points. This is because day 2015/08/15 has the largest amount of vehicles in the targeted area, and therefore the task publishing system has to publish more tasks to maintain the optimal route flow ratio. Regarding the cost, in the worst case (2015/08/15), the task publishing system consumes about 410,000 yuans per day to guide the vehicles in order to achieve overall system optimization. The annual cost would be around 149 million yuans, which is much less than the annual financial loss caused by congestion in Beijing, which is reportedly around 173.5 billion yuans [28], [29]. Moreover, the system can use certain vouchers or other authorised benefits to reduce the monetary cost.

V. Conclusions and Future Work

In this paper, we propose a reward mechanism to motivate and increase the possibility for involved civilians in the system to use their intelligence, and therefore forming a human intelligence augmented transportation system to improve the sensing, cooperation and pro-social behaviours in the routine transportation. With the build of a task publishing system on top of the existing ITS, the collective behaviours of participants are regulated and optimised by carrying out different

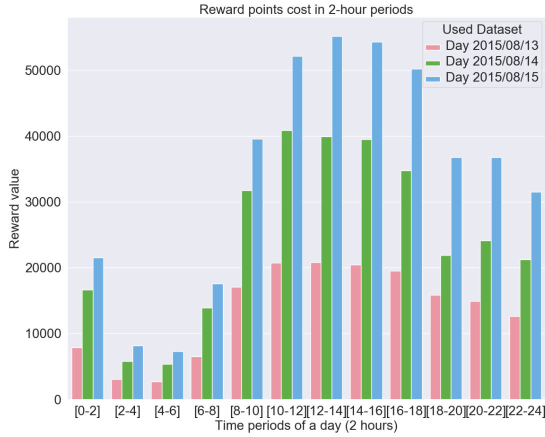

Fig. 10. The reward points cost in 2-hour periods for the task publishing system.

types of tasks. The simulation results show the average travel time of vehicles within the ITS can be significantly reduced with the aid of the reward mechanism in comparison with the non-reward counterpart. Meanwhile, the use of the reward mechanism can encourage civilians to report the dangerous situations which are difficult to be identified for the traditional sensors. Furthermore, we evaluate the cost of the task publishing system and the simulation results show that the monetary cost is only the 0.08% of the annual economic loss caused by congestion in Beijing City.

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