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A CONNECTED MOBILITY SCHEME FOR TAXI SUPPLY-DEMAND BALANCING IN A SMART CITY CONTEXT

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Abstract. In this paper we present the preliminary results of simulation-based experiments of an integrated scheme that has been proposed to control taxi supply-demand imbalance in the context of a smart city with multiple taxi operators and using Connected Mobility. We particularly explore the difference between centralized and decentralized implementations of the scheme as well as between collaborative and competitive attitudes of connected taxis. Our results show that by sharing knowledge about supply-demand imbalance and adopting a collaborative attitude, connected taxi systems can improve the performance of the service across a city by achieving a better supply-demand service balancing while improving their profits.

Keywords: Taxi supply-demand imbalance, connected mobility, smart city

1 INTRODUCTION

The spatio-temporal dynamics of taxi systems are driven by complex interactions between service suppliers and service consumers. Governments and taxi operators are continuously concerned by understanding these interactions in order to balance service supply and demand. While taxi operators need to deploy their fleets at the right spatio-temporal locations to minimize their operational costs and maximize their profit, governments need accurate estimations on taxi services' distributions over time and space for effective entry regulation and congestion control [27]. Given that taxi market is highly regulated, the prevalent literature on taxi Supply-Demand (S-D) balancing addresses the taxi equilibrium problem at a global level, consisting in balancing S-D through the regulation of taxi fleet sizes and service prices in a way to find a trade-off between passengers' benefits (taxi fare and average waiting time) and operational costs (taxis' operational costs and revenues) [19]. These approaches are often implemented using analytical models and using statistical estimations of macro indicators, commonly collected from data surveys, such as population density, number of workers, real income, number of taxis trips, etc.

Recent advances in pervasive computing and big data analytics made possible the collection and analysis of large volumes of historical spatio-temporal (GPS) data about taxi trips in many cities. Interestingly, different studies of historical spatio-temporal taxi data sets have revealed the existence of imbalance/mismatch (shortage or excess) between the supply and demand of taxi services in many cities, such as Singapore [20], Shanghai [24], Shenzhen [17], Seoul [32] and New York [37], and this despite the fact that taxi operators in these cities were using dispatching centers. Moreover, these studies have shown that S-D imbalances vary in space and time across cities [37], from which researchers have learned that even though current dispatching systems help to find optimal local solutions, they do not necessary lead to balanced S-D at a large scale (such as a city). These findings have led to a new topic in the taxi transportation state of the art, which is the study of how the imbalance between supply and demand of taxi services varies in space and time, a topic that we refer to as S-D spatio-temporal imbalance. The new topic was motivated by the fact that previous research works focused on understanding and predicting supply and demand separately, while efficient balancing requires considering both of them [21].

Several research works have been proposed over the last years to address different aspects of S-D spatio-temporal imbalance, most of them addressed the problem of identifying S-D imbalance from historical taxis trip datasets, few have addressed the problem of predicting short-term S-D imbalance, while others have been interested in understanding the factors leading to S-D imbalance. The existing works present several limits. First, there is no unified definition of S-D imbalance, and every work has used its own interpretation and definition of the concept. Second, most of the existing works implicitly model service imbalance through its manifested consequences, i.e., 1) longer customer's waiting time and 2) longer vacant taxi cruising time. Third, few works have been proposed to implement dispatching and cruising solutions for the mitigation of S-D spatio-temporal imbalance.

In a previous work [8] we proposed a spatio-temporal framework for modeling, monitoring and controlling taxi S-D imbalance at the operational, city-level scale. The framework allows to collect and process data about taxis' S-D imbalance at three levels: micro (immediate individual taxis surroundings), meso (single taxis' operator) and macro (multiple operators in a city) levels. In this paper we report our initial results on the implementation of the framework. More precisely, we tackle the problem of taxi S-D operational balancing from a connected mobility perspective, and we explore how such an approach could improve the existing state of the art regarding the problem of taxi S-D imbalance. To the best of our knowledge, no previous research works have tackled this problem from a connected mobility perspective. The remainder of the paper is structured as follows. In Section 2 we present a brief overview of the state of the art with respect to the problem of taxi S-D spatio-temporal imbalance's identification and mitigation using pervasive technologies. In Section 3 we present our proposed scheme for using Connected Mobility and X2X communication approaches to tackle the problem of taxi S-D imbalance in the context of a smart city. We model the imbalance phenomenon using the concept of service redundancy, and we present how redundancy information is calculated and aggregated in Section 4. In Section 5 we present the experimental scenarios that we implemented within the proposed scheme, and we report the results of our initial simulation-based experiments of these scenarios in Section 6.

2 STATE OF THE ART

Taxi service S-D imbalance corresponds to situations where supply and demand are not balanced. The term imbalance refers to either a situation of service shortage (service demand is higher than service supply) or service excess (service demand is less than service supply). In simple words, service shortage (respectively, service excess) happens when the number of taxi requests exceeds (respectively, is below) the number of available free taxis at a given spatio-temporal moment. Even though the term "imbalance" is widely used, the terms "mismatch" [24], "deficiency" and "gap" [36] have also been used in different research works to refer to the same concept.

Most of the research works addressing spatio-temporal taxi S-D imbalance focused on the detection and analysis of imbalance situations from historical datasets. In most of these works, imbalance has been implicitly measured using different variables as Key Performance Indicators (KPIs). Based on GPS taxi datasets, authors in [20] used the average occupancy rate and median passenger waiting time in every region of a city to estimate the imbalance. High waiting time and occupancy rate mean that customers are struggling to get free taxis and taxis are occupied, i.e., demand exceeds offer (service shortage), while low waiting time and occupancy rate mean that supply exceeds demand (service excess). Authors in [21] defined the probability p that a free taxi finds a demand within a single time unit in a given region. High probability means that free taxis can easily find a customer, which corresponds to a situation of demand exceeding supply (service shortage), while low probability values correspond to the situation of over-supply (service excess) [21]. A similar approach was used in [12] which proposed to measure imbalance using free taxi taken (FTT) probability and taxi booking ratio (TBR). Authors in [24] calculated spatio-temporal mismatch values using 1. the average empty time, reflecting how fast a free taxi can find a passenger and 2. the Average Occupied Trip Speed, reflecting the actual traffic situations as a context. Authors in [30] used a negative binomial regression model to identify the mismatch between the demand for taxi service and the availability of taxis over different regions of New York city at different daily periods. Authors in [32] used two types of hot spots to identify S-D mismatch in Seoul (Korea): 1. hot spots of free taxis routes representing taxi service supply, and 2. hot spots of points where free taxis become occupied as an indicator of the demand. Supply and demand hot-spots maps are visually compared to evaluate and identify S-D mismatched zones. Authors in [1] used the number of customers who could not find free taxis as an indicator, while authors in [36] used the umber of passengers who launched orders in taxi booking app but have not received responses. A similar approach is used by [26] which calculated the number of invalid orders, i.e., the number of taxi orders that have not been answered by taxi drivers during a given time interval. Authors in [36] defined imbalance as the total number of unsatisfied orders in each region an each time interval, which is similar to the work of authors in [14] who calculated the number of unmet orders, i.e., orders which are not responded within a given time window.

While most of the existing works have focused on the definition and the identification of taxi S-D spatio-temporal situations, only few works have addressed the problem of using S-D mismatch information to support taxis dispatching. Authors in [21] used a real-time heat map of estimated S-D imbalance with different colors visualizing different levels of S-D imbalance to the drivers of a taxi operator in Singapore. Taxi drivers can access the heat map to decide the regions where they can easily find customers [21]. Authors in [15] proposed a citywide taxi dispatching algorithm taking into consideration demand uncertainties. The proposed algorithm aims to achieve a balanced distribution of free taxis over the different regions of a city. The algorithm estimated the S-D ratio for every region in the city, and used this information to implement a dispatching algorithm with the objective of balancing taxis in all the regions of the city. A similar approach is used in [28], where taxi demand and supply are estimated for every area of a city and used to dispatch taxis across a city areas.

To conclude this section, most of the existing works have focused on the identification of taxi S-D imbalance situations using different KPIs. Imbalance situations are implicitly defined as service shortage or excess, but it is not possible to measure and quantify the imbalance itself. In addition, relatively few works have addressed the problem of imbalance mitigation, where the information about taxi service mismatch is used to implement taxi dispatching systems that allow for keeping S-D balanced across a city in a dynamic way. Particularly, the proposed algorithms are designed for individual taxi-operators, and, to the best of our knowledge, there are no available solutions that address the problem of taxi S-D balancing in the context of a smart-city with multi-operator taxis system, especially using a connected mobility architecture.

3 CONNECTED MOBILITY SCHEME FOR THE CONTROL OF TAXI SERVICE SUPPLY-DEMAND

In this paper we use a Connected Mobility-based framework that collects, analyses and controls taxi S-D imbalance in a smart city context. Imbalance corresponds to either service shortage or service excess. Service shortage (respectively, service excess) happens when the number of taxi requests exceeds (respectively, is below) the number of available free taxis at a given spatio-temporal moment. The framework extends a previous work [8] where we proposed an approach for taxi S-D imbalance modelling using the concept of service redundancy [7]. Intuitively, if the number of free taxis exceeds the number of requests in a specific spatio-temporal location, we say that the transportation services of the smart city are redundant in that location. Consequently, the smart city platform aims at keeping the service redundancy as low as possible across the city areas by relocating the free taxis at the right place at the right time. Assuming that a city is divided into a set of non-overlapping spatial regions, we model citywide taxi service redundancy as an explicit spatio-temporal phenomenon that varies across space (regions) and time, and proposed a collaborative scheme for spatio-temporal taxi service redundancy calculation, collection, and control at three different levels: micro, meso and macro (Figure 1). At the micro level, taxi service redundancy (imbalance) is calculated at the immediate surrounding of every individual connected taxi. Connected taxis make their own assessment of the service redundancy based on the density of neighboring taxis as well as on their own experiences. Based on this assessment, they decide on the action(s) to be carried out in order to deal with the imbalance situation (e.g., relocate, stop offering the service, etc.). At the meso level, imbalance at every spatial region of the city is calculated for every taxi operator based on the number of its idle taxis and the number of requests at that region during different time steps. At every spatial area, taxis of the same operator form a cluster and select a Head-of-Cluster (HoC) which continuously receives and aggregates data from the taxis that are members of its cluster. The HoC has also access to the information about the current requests emitted by the service consumers located at the same spatial area as the cluster. Based on all the data received, the HoC can generate a picture about the situation of service redundancy (imbalance) within the area where its cluster members are deployed. At the macro level, service redundancy is calculated for every spatial area of the city considering all taxi operators. For this purpose, a controller, an autonomous smart city resource, is assigned to every spatial area to collect data from the HoCs, customers, as well as the Intelligent Transportation Systems' infrastructure of the smart city (e.g., traffic light) on a regular basis and/or on-demand. Based on this information as well as on additional feedback from customers, the controller issues recommendations about redundancy to taxi operators (HoCs) as well as to neighboring controllers in order to balance the S-D across the city.

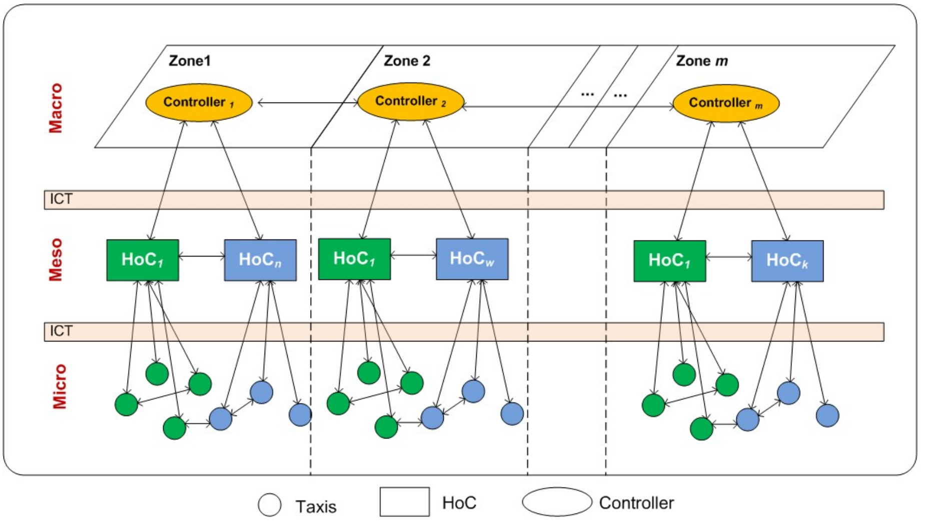


Figure 1. Connected Mobility and X2X communication environment for taxi service redundancy control

From a social perspective, the entities of the framework can have different behaviours depending from the application scenarios. As a matter of fact, connected taxis of the same operator can use their own assessment of the situation to decide either to collaborate with or to compete against each others, and to cooperate or not with their corresponding HoCs. However, they intuitively tend to compete with connected taxis belonging to the other taxi operators. Neighbor HoCs (located in neighboring areas) belonging to the same taxi operator tend to collaborate in order to balance the redundancy of their taxis and improve their services, while HoCs from different operators tend to compete to maximize the benefits of their mutual members. Like connected taxis, HoCs can decide to comply or not to the recommendations of the controllers, who are expected to collaborate with each others in order to keep the service S-D balanced across the city. Within such a framework, communications are extended from Vehicle-to-Vehicle – V2V (connected taxis of the same operator, HoCs) to Vehicle-to-Space – V2S (HoC Vehicle to Controller), Vehicle-to-Infrastructure – V2I (for example to collect data about traffic conditions and estimating when services would be available), Space-to-Space – S2S (for collaboration and competition between the spatial areas, through controllers), Infrastructure-to-Infrastructure – I2I, and Infrastructure-to-Space – I2S (Figure 1).

Previous experiments [8] showed that using redundancy-aware dispatching (dispatching free taxis from areas with service excess to areas with service shortage) allowed for improving the balance of taxis service across all the regions of a city, compared to traditional dispatching where redundancy information is not used. In this paper we test the performance of the framework proposed in [8] in the context of Connected Mobility and X2X communication environment. We particularly report our preliminary results regarding the difference between collaborative and competitive social behaviours as well as centralized and decentralized implementation of the framework. But before presenting these results, in the following section we present how redundancy data are calculated and aggregated within the three-level framework.

4 REDUNDANCY DATA AGGREGATION

In this section, we outline the redundancy data aggregation scheme with respect to the proposed architecture. The proposed scheme infers multi-scale redundancy data aggregated using a bottom-up approach, where micro-level redundancy is calculated first, then aggregated into meso-level redundancy, which is in turn aggregated into macro-level redundancy.

4.1 Micro-Level Redundancy Calculation

Redundancy data is calculated at a micro level from the perspective of individual taxis. Let us denote by N_c the number of customers in the immediate vicinity of the taxi and let us denote by N_t the number of vacant taxis. The S-D mismatch referred to as the redundancy is calculated using $\rho_i = \frac{N_c^i}{N_t^i}$. To model overlapping clusters of customers, we assign a positive weight ω_{ij} of a customer i belonging to the immediate vicinity of the taxi j. This weight is calculated based on the distance between i and j denoted by δ_{ij}.

$$\omega_{ij} = \frac{\delta_j - \delta_{ij}}{\delta_j}, \tag{1}$$

where δ_j is the perception radius of the taxi j.

Similarly, we define ω^{kj} the weight corresponding to the likelihood of a taxi k being idly cruising within the immediate vicinity of a taxi j.

$$\omega^{kj} = \frac{\delta_j - \delta^{kj}}{\delta_j}. \tag{2}$$

Therefore, the micro-redundancy perceived by a taxi j is computed using the following equation:

$$\rho_j = \frac{\sum_{i=1}^{N_C^j} \omega_{ij}}{1 + \sum_{i=1}^{N_t^j} \omega^{kj}}. \tag{3}$$

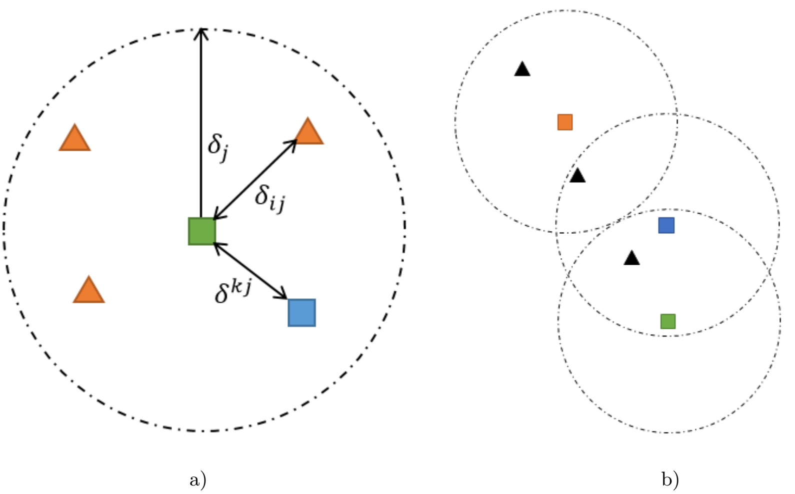


Figure 2. Mirco-level redundancy calculation scheme. The distances used to calculate the S-D proximity a) and an example of three cases of redundancy levels are depicted in b) low redundancy for the orange taxi, high redundancy for the green taxi and moderate redundancy as perceived by the blue taxi.

Figure 2 illustrates an example of micro-level redundancy calculation, where triangles and squares represent customers and taxis, respectively.

4.2 Meso-Level Redundancy Aggregation

At the level of each taxi operator/company, and with respect to the served region, the micro-level information is aggregated to infer meso-level redundancy information. Let us denote by $\mathcal{T}_{C_r} = \{t_1^C, \dots, t_{N_r}^C\}$ the set of taxis operating in the region r for the company C.

Over a specific time interval preset by the taxi company, the redundancy data that have been collected by the taxis t_j^C, $1 \leq j \leq N_{C_r}$ are combined. Each taxi operator assigns a head of cluster (HoC) to the region of interest r denoted by $\mathrm{HoC}^{\mathrm{C_r}}$. Each taxi reports the redundancy data perceived from its micro-level standpoint to the head of cluster. The reporting periodicity does not necessarily have to be regular for various reasons including the intermittent connectivity, the acquiescence of the drivers regarding the data sharing schemes, malfunctioning sensing devices, etc. Therefore, we assume that the redundancy data is aggregated over different time intervals $[\tau_i, \tau_{i+1}]$ such that $\cup_{i=1}^{t-1}[\tau_i, \tau_{i+1}] = [1, t]$ is the total time period during which $\mathrm{HoC}^{\mathrm{C_r}}$ aggregates the meso-level redundancy data.

Each $\mathrm{HoC}^{\mathrm{C_r}}$ assigns a weight for each taxi t_j^C, $1 \le j \le N_{C_r}$ denoted by ν_j^C corresponding to its proximity to the boundaries of the region r. The meso-level redundancy ρ_{C_r} is calculated as a weighted sum of the micro-level redundancy data ρ_j using the following equation:

$$\rho_{C_r} = \frac{1}{t} \sum_{i=1}^{t-1} \frac{(\tau_{i+1} - \tau_i)}{N_{C_r}^i} \sum_{j=1}^{N_{C_r}^i} \nu_j^{C_r,i} \rho_j^i \tag{4}$$

where ρ_j^i, $\nu_j^{C_r,i}$ and $N_{C_r}^i$ refer to the micro-level redundancy perceived by a taxi j, the weight representing the proximity of a taxi j belonging to a company C to the boundaries of the region r and the the total number of taxis operating with C in the region r for a specific period of time $[\tau_i, \tau_{i+1}]$ respectively.

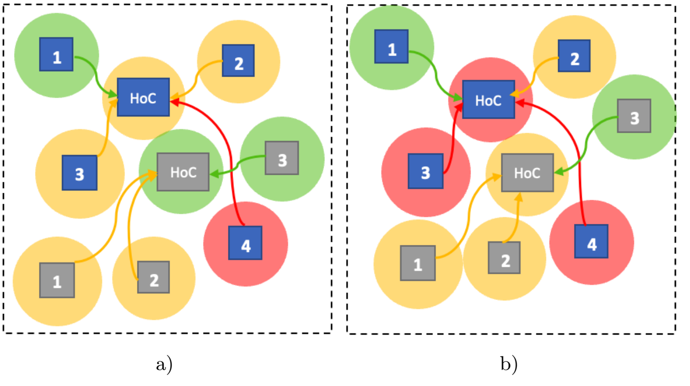


Figure 3. An example of meso-level redundancy aggregation with four taxis operating in a region delimited by a dashed line. Two levels of redundancy are calculated during two different time intervals a) then b). Taxis are represented by squares with two different colors depicting two taxi companies operating in the same region and redundancy levels are depicted using three colours: green (moderate), orange (high/low) and red (critically high/low).

Figure 3 illustrates an example of meso-redundancy aggregation. In Figure 3 a) the meso-redundancy of the gray company is moderate (green) because taxis 1 and 2 are closer to the boundaries of the region than taxi 3, and consequently taxi 3 has the highest weight in the meso-redundancy calculation over them. The situation has changed in Figure 3 b) because taxis 1 and 2 moved away from the boundaries, leading to their weights increased over taxi 3, and the meso-redundancy level of the gray HoC switched to high/low (orange).

4.3 Macro-Level Redundancy Aggregation

At the macroscopic scale (city-wide, multi-operator), each region controller polls the head of clusters operating within the monitored zone to update the overall redundancy pertaining to the S-D mismatch. Unlike the meso-level, the macro-level redundancy is updated on a regular basis. Each zone controller requests the associated meso-level HoCs to send their redundancy data ρ_{C_r}. The controller compares the updated redundancy data at each zone with the previous values. We denote by $\Delta_n(\rho_{C_r})$ the redundancy variation during the time interval $[\mathbf{t_n}, \mathbf{t_{n+a}}]$. To avoid fortuitous fluctuations of redundancy that may have been caused by temporary conditions (e.g. weather condition), the controller sets a threshold for updating the redundancy value denoted by ε_r. Hence, the redundancy value is changed at a macro level if and only if $\Delta_n(\rho_{C_r}) > \varepsilon_r$.

5 IMPLEMENTATION SCENARIOS

Using the Connected Mobility scheme presented in Section 3, a new taxi dispatching algorithm has been designed based on the concept of service redundancy presented in Section 4. The main idea of the algorithm consists at relocating free taxis from areas with high redundancy to areas with low service redundancy, which allows for achieving a better balance of S-D across the city. The details of the proposed relocation algorithm is out of the scope of this paper. In order to test the performance of the proposed Connected Mobility and X2X communication framework, two aspects have been explored. The first concerns the architectural implementation of the three-level redundancy calculation and aggregation. With this respect, we aimed to compare between centralized and decentralized implementations. The second aspect concerns the social behaviour of the involved entities (connected taxis, HoCs and Controllers), and we explored the differences between collaborative and competitive behaviours.

5.1 Centralized vs. Decentralized Implementation

From an architectural perspective, we implemented two different communication scenarios: 1. centralized and 2. decentralized.

In the centralized implementation scenario, the calculation of the micro-level redundancy and the aggregation of the meso-redundancy and macro-redundancy are performed by controllers of every spatial area (zone). We assume that all connected taxis and customers are equipped with GPS and their positions are accessible to the controllers. In the decentralised (distributed) scenario, the calculation of the micro-redundancy, meso-redundancy and macro-redundancy are performed according to a distributed deployment. As presented in Section 4, micro-redundancy calculation is performed by individual taxis, meso-redundancy calculation is performed by Head-of-Clusters and macro-redundancy is calculated by controllers of every spatial zone. Redundancy-data exchange is possible either through direct communication between individual taxis and their HoCs (respectively, HoCs and their controllers) or through the communication channels of the sensing infrastructure of the X2X environment.

It is worth mentioning that the service redundancy classification (moderate, high/low, critically high/low) is performed at the level of every taxi operator as well as at the city-level (considering all taxi operators) according to the machine learning classification algorithm proposed in [8].

5.2 Collaborative vs. Competitive Taxis

With respect to the behavior of connected taxis, two scenarios of redundancy-based dispatching implementation have been identified: 1. collaborative and 2. competitive taxis.

The objective of investigating these scenarios is twofold: First, we assess the impact of taxi drivers compliance with the recommendations of the HoC on the mitigation of redundancy and second, we evaluate the implications of the collaboration extent on the profits.

In the collaborative scenario, we assume that individual taxis operating with an operator (micro level) share their knowledge about micro service redundancy with their HoC. The HoC of every spatial area uses this knowledge to update and build its view of service redundancy in that zone, and then makes dispatching recommendations to the individual taxis in order to balance the S-D redundancy of its company at that specific spatial area. We assume that free taxis follow the recommendations of their HoCs and plan their next destination accordingly. For the sake of simplification, we assume that the drivers discard their prior experience and totally comply with the HoC when they receive instructions and/or recommendations to relocate or to adjust their operational strategies.

In the competitive scenario, we assume that individual taxis of every taxi operator (micro level) share their knowledge about micro service redundancy with their HoC but do not follow its relocation recommendations. Instead, every vacant individual taxi plans its next destination according to its own knowledge about micro-level redundancy. From an application perspective, the drivers are aware of the local redundancy level and yet they are reluctant to follow the recommendations issued by the HoC and prefer to use their own operational strategies based on their personal experience.

6 EXPERIMENTAL STUDY

In this section we present an experimental study that we implemented to explore the performance of the proposed scheme and test the proposed implementation scenarios. The geographic area that we considered corresponds to the city of Salalah, Oman. Data about taxi supply and demand have been collected from different sources and using different techniques. Data from all fix taxi stands in the city (airport, shopping malls, hospitals, etc.) have been collected through real observations. In every stand, observations about hourly numbers of waiting taxis (supply) and requests (demand) were recorded over a period of one week, from 8 am to 8 pm. The distribution of taxi demand across the different areas of Salalah city for typical days of the week has been defined based on the population densities in these areas. A geographic environment of the city has been especially generated containing an updated road network (roads, directions and speed limits), the main semantic zones (commercial, residential, etc.) and the main Points of Interest (PoI) (hospitals, shopping malls, hotels, coffee shops, etc.) (Figure 4). All these data have been used to improve the simulation model used in [8]. Taxis demand has been generated using a Poisson process with variable rates. The arrival rates are randomly assigned to destinations (road intersections, zones or PoIs) on an hourly basis. Each demand corresponds to a route from an origin to a random destination. The simulation time step is one minute, but we calculate and generate macro-level redundancy maps every 60 minutes (by default, but it can be changed accordingly as an input simulation parameter). The geographic space of Salalah city has been divided into 10 administrative areas, and every area is divided into a grid of cells (zones) whose dimensions can be set by the user (by default it is $500\,\mathrm{m} \times 500\,\mathrm{m}$ cells). Within this spatial decomposition, macro-redundancy is calculated for every one of the zones (cells) and taking into consideration all taxi operators, meso-redundancy is calculated for each of the three taxi operators at every cell, and micro-redundancy is calculated for very individual taxi at every cell (Figure 5).

We performed the simulation experiments using an agent-based model that we implemented with the GAMA platform [6]. In order to simulate the network communication between the X2X environment objects, all the objects (taxis, HoCs and controllers) have been implemented as agents that can communicate together using the exchange of messages and network communication functionalities of the platform.

The preliminary results of the current simulation experiments are as follows.

6.1 Collaborative vs. Competitive Redundancy-Based Dispatching

Table 1 illustrates the preliminary results that compare the performance of the two redundancy-based dispatching algorithms. We can see that the collaborative scenario leads to a better average waiting time and consequently a better customer satisfaction. These results demonstrate the potential benefit of having a big picture view (at both meso and macro levels) of the supply-demand redundancy

Figure 4. The geographic stretch of the simulation environment of Salalah city containing the road network (lines), semantic zones (polygons) and PoIs (circles)

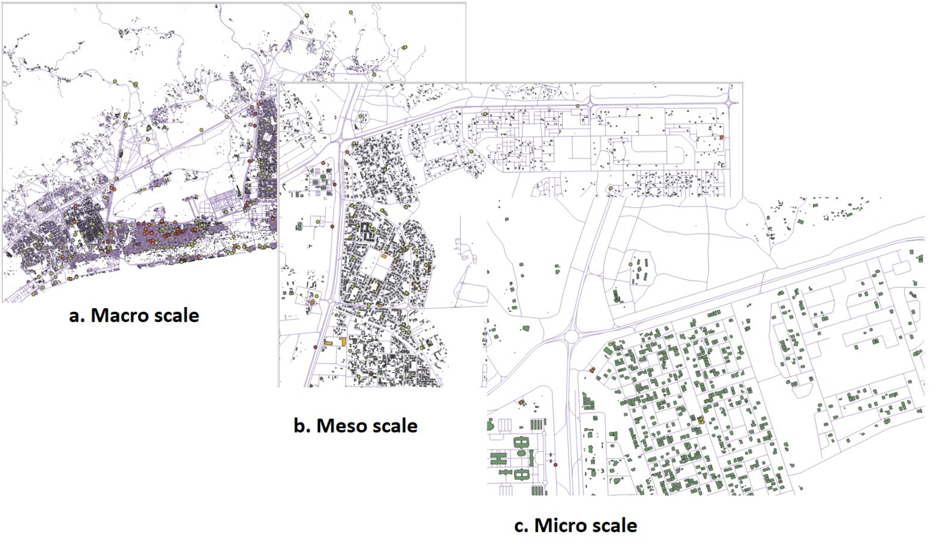


Figure 5. The spatial decomposition of the city of Salalah into macro (all areas), meso (individual areas) and micro (any position inside a given area)

and how it can be used to improve the performance of taxi service in a smart city.

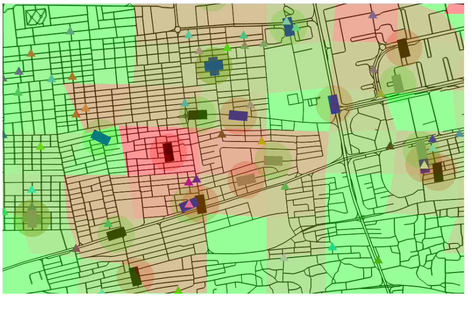
Scenario	Average Waiting Time (in Minutes)	Average Idle Driving Time (in Minutes)	Percentage of Missed Customers	Customer Satisfaction Level
Competitive	5.3	17.8	13 %	80 %
Collaborative	4.5	19.6	10 %	87 %

Table 1. Current performance of competitive and cooperative scenarios

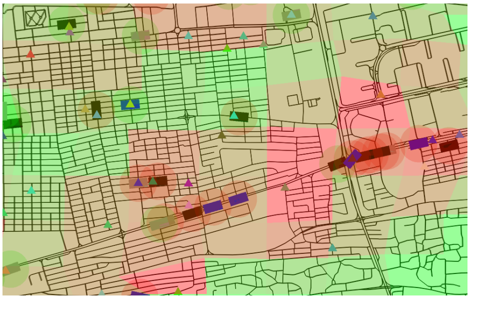
Figure 6 illustrates snapshot maps showing the distribution of macro-level redundancy in one administrative area and at two different days for both collaborative and competitive scenarios. The time interval between 14:00 and 15:30 corresponds to the afternoon traffic peak in Salalah city, and we can see that with the collaborative scenario, supply-demand is moderately balanced across the different zones of the area, while the competitive scenario leads to a medium and critical imbalance situation in most of the area's zone.

a) Day, 3 14:00 – Collaborative scenario

b) Day, 3 15:30 – Collaborative scenario



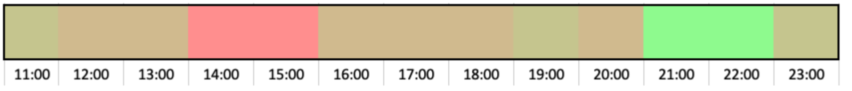
c) Day, 6 14:00 – Competitive scenario



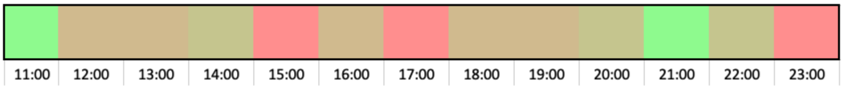
d) Day, 6 15:30 – Competitive scenario

Figure 6. Macro-level redundancy map in the same zone at two different days and hours. a) and b) depict the redundancy outcome using a collaborative scenario while c) and d) illustrate the outcome of a competitive scenario. Red cells correspond to critically high/low redundancy, amber to medium redundancy and green to moderate redundancy. Circles represent meso-level redundancy values calculated by the different clusters in every spatial zone.

Figure 7 shows the hourly evolution of the macro-redundancy situation at a specific zone (zone Z13) for the collaborative and competitive scenarios. We can see that the collaborative scenario leads to a gradual transition of the situation between moderate and critically imbalanced, while the competitive scenario leads to a random variation of the situation between the two extremes. Obviously, the collaborative scenario yields to a better control of the S-D balance over the competitive one.



a) Day 1, 11:00–23:00 – Collaborative scenario



b) Day 8, 11:00–23:00 – Competitive scenario

Figure 7. Evolution of the macro-level redundancy in zone Z13 for a 13-hour period using collaborative a) and competitive b) scenarios

To illustrate the importance of stakeholders compliance with the redundancy mitigation scheme, Figure 8 depicts the variation of average profit gained by a taxi company operating in zone Z13 during the same time interval spanning from 11:00 up to 23:00. The reported average profit suggests that redundancy intrinsically impacts the average profit.

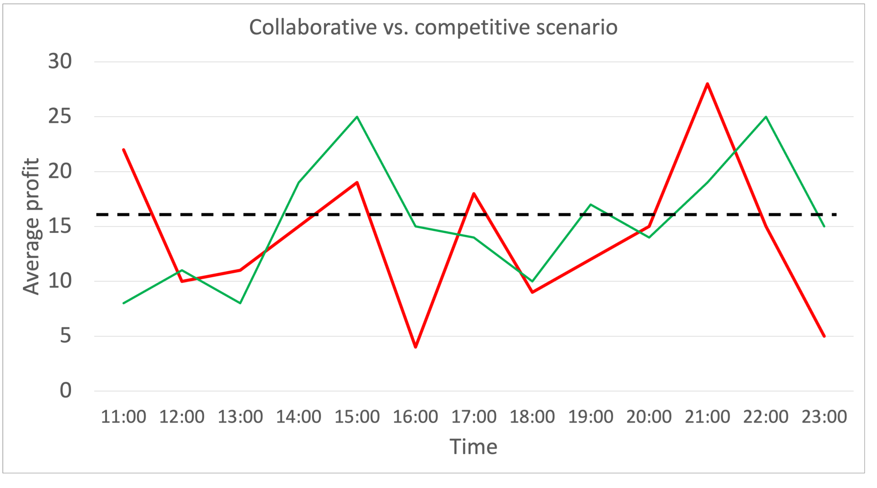


Figure 8. Average taxis profit in zone Z13 using collaborative (solid green) against competitive scenario (solid red). Overall average profit is illustrated by the black dashed line.

6.2 Centralized vs. Decentralized Redundancy Calculation Schemes

Table 2 illustrates the preliminary results of the simulation-based experiments that we implemented to test the performance of the proposed redundancy control framework according to a centralized and distributed deployment. These results correspond to averages of multiple simulation runs. Even though the calculation times are high because of the problem complexity and further optimization work is required in the future, we can see that a decentralized implementation yields better calculation times for all micro, meso and macro levels, as expected. However, network communication delay has not been considered in these results, which needs to be evaluated with a real testbed in order to assess the effect of the real environment constraints on the performance of the proposed scheme.

Architecture	Number of Taxis	Micro-Redundancy Calculation Time	Meso-Redundancy Calculation Time	Macro-Redundancy Calculation Time
Centralized	100	15	27	34
	200	35	43	50
	300	46	65	81
Distributed	100	5	16	19
	200	11	34	32
	300	19	45	63

Table 2. Current performance of Centralized and Distributed redundancy control schemes. Calculation times are reported in seconds.

7 CONCLUSION

In this paper we proposed a connected-mobility scheme for taxi S-D balancing in the context of a smart city where S-D imbalance information is calculated at three hierarchical levels, micro, meso and macro. The the preliminary results of our simulation-based experiments show that by sharing knowledge about supply-demand imbalance in a collaborative attitude, connected taxi systems can improve not only their own profits, but also the S-D balance across a city.

While our preliminary results are promising, more experiments are required in the future in order to generalise the competitive and collaborative scenarios at the level of taxi operators and/or controllers. Also, the experiment results show high calculation times of micro, meso and macro which represents a scalability concern for the implementation of the proposed framework in a real environment. To solve this issue, we are currently implementing our experiments with different connected mobility simulators and we are working on a testbed to evaluate the performance of the proposed scheme under real-environment communication constraints.

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