

Data Pricing Framework for Intelligent Transportation Systems

S. Emre Alptekin
Industrial Engineering Department
Galatasaray University
Ciragan Cad. No.36 34357 İstanbul
TURKEY
ealptekin@gsu.edu.tr

Abstract: - Ubiquitous sensing a critical enabler for intelligent transportation systems is becoming a reality due to recent advancements in wireless sensor networks. Internet of Things paradigm provides the necessary tools to define how the information should be gathered and shared across different platforms. Intelligent transportation systems, effected by this transformation provides wide range of applications in areas such as routing, smart logistics, assisted/autonomous driving, environmental monitoring etc. These applications require a high level of initial investment in terms of infrastructure. Therefore, efficient resource management and service pricing is essential for attracting the customers who will use and/or share data provided by the platforms/customers. The mechanisms in place have to manage efficiently the flow of data on possibly unpredictable network conditions. Data pricing, an instrument that captures users' utilities, provides users' right economic incentives and manages network congestion especially in high demand periods. In this paper, a framework based on game theory with a data exchange regulator is proposed to deal with data pricing. The framework considers effects of price and quality variations on demand hence on utilities of service providers. The provided case study demonstrates applicability of the proposed methodology.

Key-Words: - Game theory, intelligent transportation systems, Internet of things, pricing mechanism

1 Introduction

The Internet of Things' (IoT) promise of "smart, connected" products offer huge opportunities for new functionalities and capabilities and possibly disrupt value chains and force companies like General Electrics, Google, Amazon, etc. to reshape their product/service offerings. They have to come up with new sets of strategies to define how value is created [1]. The most basic element of this new phenomenon is the data generated as a byproduct and once again fed into the system to enhance the product/service. IoT possibly could contribute in areas of assisted living, e-health, enhanced learning, automation, industrial manufacturing, logistics, business/process management, intelligent transportation of people and goods [2]. However, it is for a typical disruptive technology, IoT necessitates new scenarios and product propositions. It requires some sort of intelligence to be embedded into the framework to connect everyday existing objects [3]. As foreseen by Gubbi et al [3], IoT requires: "(1) a shared understanding of the situation of its users and their appliances, (2) software architectures and pervasive communication networks to process and convey the contextual information to where it is relevant, and (3) the

analytics tools in the IoT that aim for autonomous and smart behavior." These requirements are actually transforming even product-oriented organizations into service providers along with their product offerings. If organizations were able to deliver in all these aspects, the outcome would be smart connectivity and context-aware computation.

In literature, there are works describing possible effects of IoT on Intelligent transportation systems. Atzori et al. [2] suggest that IoT will help to better route traffic, monitor the status of goods in movement in real-time along the supply chain, avoid collisions, monitor transport of hazardous materials, regulate traffic jams and improve efficiency of food supply chains in prolonging shelve life [2]. Ibanez et al. [4] discuss possible goals that should be part of any intelligent transportation system, and categorize them as safety and personal security, access and mobility, environmental sustainability and economical development. These goals require minimization of CO₂ emissions, improvement of traffic efficiency, and road safety, as well as reduction of vehicle wear, transportation times and fuel consumption. [4] Ibanez et al. also define intelligent transportation systems with IoT: radio frequency identification tags and readers, sensor

technologies, which will be used collect information about traffic conditions in the environment. These sensors should detect speed, direction, travel times, send this information for further analysis, in order to make intelligent decisions such as dynamic traffic light management and changing of number of lanes [4].

However, the development of such a framework is not straightforward. Integration of information and communication technologies along with the implementation of adequate and necessary technologies and infrastructures in vehicles, roads, streets and avenues is a prerequisite [4]. The initial step for integration should deal with the large amount of data, that is usually kept in independent databases, to be collected, processed and fed back on real-time if possible to the users' of the system.

As demonstrated by Hoang and Niyato [5], processed information delivered as a service to customers, may establish new revenue streams for intelligent transportation system service providers. However, the quality of service levels in case of intelligent transportation systems suffer from possibly constrained network conditions. Sen et al. [6], with their "smart data pricing" mechanism, aimed to understand users' behaviors and proposed dynamic adaptation to different network traffic conditions using economic models for computing prices.

In this work, a framework for sensor data management and service price competition among data providers in smart transportation systems is proposed. The framework aims to optimized providers' utility functions by analyzing consumers' behaviors in response to price and quality level changes. Game theory is applied to calculate customer's demand along with the prices and utilities of service providers'. The applicability of the proposed methodology is demonstrated via a case study. The scenarios as part of the case study are used to illustrate the effect of different behaviors on the utilities and prices; hence, suggest a recommended action for service providers.

The remainder of the article is organized as follows: in Section 2, related literature is summarized. Section 3 presents the methodologies that constitute the proposed methodology. The details and implementation of the proposed framework is demonstrated through a case study in Section 4. Section 5 concludes the study discussing the findings and further study possibilities.

2 Related Work

Although, there are different definitions and perspectives for IoT, numerous researches define IoT as a new paradigm in an era of ubiquitous computing. Internet-oriented, things-oriented and semantic-oriented perspectives of IoT represent different aspects of the topic [2]. Hence, interdisciplinary nature of IoT effected the diversity of application domains and open research issues. Smart transportation systems, as part of IoT domain, similarly, attracts attention among research community. This section summarizes some of the recent work that formed the base of this study.

Stefansson and Lumsden [7] established the conceptual model of the smart transportation management system and analyzed how different factors change the performance of distribution activities and discussed management issues. Their framework is developed through case studies with the involvement of software providers, logistics service providers and carriers. The framework makes use of state-of-the-art vehicle information systems and infrastructure systems.

In their work, Ibáñez et al. [4] introduced emerging technologies, such as connected vehicles, wireless technologies, etc. as part of smart transportation systems. They suggested that IoT will enable seamless integration of different systems resulting in sustainable transportation solutions. They concluded their study with the discussion of integration challenges and issues faced by the transportation sector.

Niyato et al. [8], proposed smart data pricing for IoT systems and services. They defined an IoT architecture and based on the architecture they presented possible business models and suggested a pricing scheme for IoT service providers. Their model demonstrated via a case study sensing data buying and selling with cooperation among service providers. They showed that service bundling could result in a higher profit level for service providers.

Hoang and Niyato [5], proposed a business model for competitive pricing in an Internet-of-Vehicle environment. Their competitive game model obtained prices for providers through Nash equilibrium solution. They also demonstrated that repeated game models could result in higher revenues for service providers. The efficiency of their proposed model is demonstrated using simulation results.

In their work, Vardakas et al. [9] provided a comprehensive review of various demand response schemes and optimization models for the optimal

control of demand response in smart grids. They also categorized optimization models based on the objective of the optimization model, the ability to include uncertainties, scalability, responsiveness, communication requirements and support of multiple load types.

Sen et al. [6] used smart data pricing approach to control network congestion by modifying users' behaviors. Their proposition was to create right economic conditions in order to shift users' demand to less congested times or to supplementary networks. They evaluated two different pricing schemes through case studies: time-dependent pricing and traffic offloading. They suggested that smart data pricing could be readily applied to machine-to-machine communication and IoT applications.

3 Proposed Methodology

Data pricing models as reviewed by Sen et al. [6] is depending on different factors, such as, usage-based pricing / metering / throttling / capping, time / location / congestion-dependent pricing, app based pricing / sponsored access, Paris metro pricing, quota-aware content distribution, reverse billing or sponsored content. Dynamic pricing with real-time changes in prices, although applied scarcely in real-life scenarios aims to respond to network congestion and fluctuations in quality of experience of the consumers'.

Dynamic pricing necessitates setting prices based on the reactions of competition. Hence, analyzing market dynamics and behaviors of actors in the market is a prerequisite. This knowledge is usually obtained by answering questions like: "What action to choose in a competitive environment?" and "What are other companies doing?" [10].

As stated by Sen et al. [6], Niyato et al. [8] and Vardakas et al. [9], game theoretical framework is much suited for dynamic pricing scenarios. Game theory typically deals with conflict and cooperation among actors in a marketplace. It provides a basis for formulating, structuring, analyzing and understanding different strategic scenarios [11].

Game theoretical models start with the definition of actors, their preferences, their information, possible strategic actions and their outcomes in a given state. Different real-life scenarios are also explored with these models, such as the possibility of cooperation [12]. There are several intrinsic assumptions such as rationality of game's actors. A rational actor should always choose the action that

gives the most preferred result in view of the expected reactions of competitors.

In this work, as part of smart data pricing approach, a dynamic pricing model with non-cooperative nature with rational actors is assumed. Solution approach is built upon on Nash equilibrium concept. The Nash equilibrium as the name suggests defines a point where actors in a game after having chosen strategies, do not reconsider their strategies, as they are not able to increase their utilities while the other players keep all their strategies unchanged. At this point, the set of strategic choices and corresponding utilities represent the Nash equilibrium.

4 Research Framework

The decision framework used in this paper is based on game theoretical approach proposed by Işıklar Alptekin and Bener [13]. They built their model on a competitive spectrum exchange marketplace. They obtained the equilibrium spectrum prices through Nash equilibrium point, which tells the spectrum holders the ideal price and quality of service level values where profit is maximized at the highest level of customer satisfaction. They showed via numerical results that the price and QoS level values of the network providers depend on the price and QoS of their own bands as well as the prices and QoS levels of their competitors' bands.

Based on their research, the pricing problem for intelligent transportation system is formed as follows:

Players: A set of N Service providers in smart transportation network. They compete with each other to serve customers.

Strategies: The choice of price of the offered data service subject to QoS parameters and capacity constraints.

Commodity of the market: Data services.

The objective of the model is to calculate the prices of the data services that should result in highest possible utilities for service providers as well as highest possible service quality for consumers.

The proposed market architecture is given in Fig. 1. Service providers are at the top of the hierarchy. The regulatory body of the marketplace coordinates the interaction between customers and service providers and is monitoring data delivery service and possibly handling payment transactions as an intermediary. If the service providers chose to cooperate in their service offerings, the regulatory body would provide bundling of data services as a

package. However, the main assumption of the proposed model is that the service providers do not cooperate and behave independently.

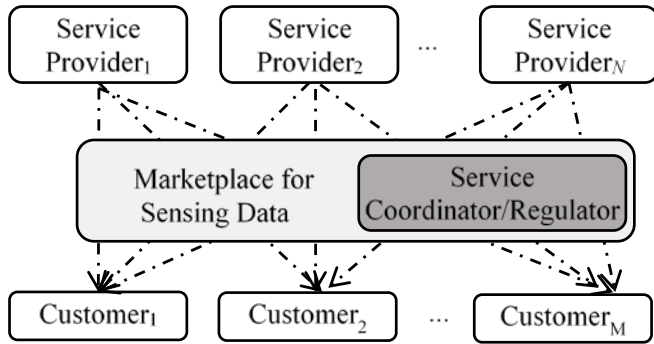


Fig. 1. The system model for data services marketplace.

As proposed by Işıklar Alptekin and Bener [13] the service providers offering has two parameters: Price and quality of service (QoS) level. $p = \{p_{1k}, \dots, p_{Nk}\}$ is the vector of prices where p_{ik} is the price that i^{th} Service Provider charges k^{th} Customer, and $q = \{q_{1k}, \dots, q_{Nk}\}$ where q_{ik} is the quality level offered by i^{th} Service Provider to k^{th} Customer with $k \in [1, M]$ and $i \in [1, N]$.

Similarly, the price is determined based on two components: A base price (\underline{p}_i) based on the demand to i^{th} Service Provider and a quality-related price (\overline{p}_{ik}) based on the quality level of i^{th} Service Provider's services. Naturally, if the demand for i^{th} Service Provider's services increase so does its base price. The same is also valid for quality levels. The base price is calculated using the following equation: [13]

$$\underline{p}_i = c_i + k_i \left(\sum_{k \in \{1, \dots, M\}} D_{ik} \right) \quad (1)$$

where c_i symbolizes the fixed costs of the i^{th} Service Provider, D_{ik} represents the demand of k^{th} Customer to i^{th} Service Provider, and k_i is a positive constant measuring the effect of base price on the demand.

The effect of QoS level on the service price is calculated as follows: [13]

$$\overline{p}_{ik} = w_{ik} \cdot q_{ik} - \sum_{\substack{j=1 \\ j \neq i}}^n w_{jk} \cdot q_{jk} \quad (2)$$

where w_{ik} is a positive constant representing the effect of QoS level on i^{th} Service Provider's prices,

q_{ik} is the QoS level offered to k^{th} Customer, and w_{jk} is a positive constant representing the effect of competitor's QoS level on i^{th} Service Provider's prices. Hence, the price offered to k^{th} Customer by i^{th} Service Provider is calculated by combining equation (1) and (2): [13]

$$p_{ik} = \underline{p}_i + \overline{p}_{ik} \quad (3)$$

The k^{th} Customer's demand from i^{th} Service Provider is obtained as: [13]

$$D_{ik}(p) = a_k - b_k \cdot p_{ik} + \sum_{\substack{j=1 \\ i \neq j}}^n t_{jk} \cdot p_{jk} \quad (4)$$

where b_k represents price changes' influence on i^{th} Service Provider's demand, t_{jk} represents competitors' price changes' effect on i^{th} Service Provider's demand. a_k is k^{th} Customer's base demand from i^{th} Service Provider. Here, customer's demand is assumed to be linearly affected by the price of the services. The price equation is obtained by combining equations (1), (2) and (4): [13]

$$p_{ik} = c_i + k_i \left(\sum_k \left[a_k - b_k \cdot p_{ik} + \sum_{\substack{j=1 \\ i \neq j}}^n t_{jk} \cdot p_{jk} \right] \right) + w_{ik} \cdot q_{ik} - \sum_{\substack{j=1 \\ j \neq i}}^n w_{jk} \cdot q_{jk} \quad (5)$$

$$0 \leq c_i \leq p_{ik} \leq p_{ik}^{\max};$$

$$0 \leq q_{ik}^{\min} \leq q_{ik} \leq q_{ik}^{\max}$$

where maximum price level and minimum quality levels are defined by the service provider itself or by the regulatory body. The lower bound for the price keeps service providers' net profit positive.

The QoS related parameters in the model (q_{ik}) are defined in the range of [0, 1]. The level of these parameters depends on many factors, such as interval of the spectrum of the band, throughput, signal-to-interference-plus-noise ratio (SINR), bit error rate (BER) degradation in the network, network access time, vulnerability to denial-of-service attack, response time, etc. [14]. Each customer or more commonly applications used by the customers will have to determine which QoS parameters to consider and what their importance weights should be.

Işıklar Alptekin and Bener [13] in their cognitive radio network model proposed that service providers

should consider their opportunity costs when setting the prices. They used the definition of Cave [15], who defined the opportunity cost as the value of an asset or resource in the next best alternative that is foregone by virtue of its actual use. In intelligent transportation system framework a similar cost may occur if a service provider has excess demand for its resources and hence use pricing to regulate its demand. In literature, there are different propositions to calculate opportunity cost especially in the context of spectrum management. In this paper, Doyle's research [16] will be used to determine the opportunity cost of i^{th} Service Provider received from k^{th} Customer: [13]

$$OC_{ik}(D_{ik}) = [t_{1ik} \cdot BF_k + t_{2ik} \cdot LF_k] \cdot D_{ik} \cdot p_{ik} \quad (6)$$

where BF_k is defined as the technology factor, and LF_k as the location factor in the range of [0-1]. The technology factor represents the number of technologies used by the service providers to reach its customer, such as cellular networks, Bluetooth, machine-to-machine communication, etc.. If this factor is higher, it simply means service provider has increased opportunity to reach customers. The location factor determines the congestion level of the region that service providers operate. The weights, t_{1ik} and t_{2ik} , are used to modify the cost value according to the marketing preferences of service providers, where t_{1ik} and t_{2ik} are positive and their sum is set to equal to one.

The utility functions of the service providers depend on their price and QoS level strategies. The utility function of the i^{th} Service Provider is represented by $U_i(p_{ik}, q_{ik})$ and given by the sum of the differences of its opportunity cost (OC_{ik}) from its revenues from all its customers:

$$U_i(p, q) = \sum_{k \in \{1, \dots, M\}} [p_{ik} \cdot D_{ik} - OC_{ik}(D_{ik})] \quad (7)$$

For every service provider in the marketplace, the utility function U_i 's value depends on the strategy selected by i^{th} service provider given as (p_i, q_i) , and the current strategies of its competitors given as (p_{-i}, q_{-i}) . In this paper, it is assumed that $U_i(p, q)$ is continuous in p and concave in p_{ik} for all $i \in [1, N]$ and $k \in [1, M]$.

$U_i(p, q)$ represents the net revenue of i^{th} service provider with the vector of prices p and the vector of QoS parameters q , where QoS levels is fixed at values $q_{1k}, q_{1k}, q_{2k}, \dots, q_{Nk}$ during the game. The resulting single-parameter Nash equilibrium in p at q is the vector p^* that solves for all i : [13]

$$U_i(p^*, q) = \max_{(p_{ik}, q) \in \mathfrak{R}_i} U_i(p_{1k}^*, \dots, p_{ik}^*, \dots, p_{Nk}^*, q_{1k}, \dots, q_{ik}, \dots, q_{Nk}) \quad (8)$$

According to the research of Başar and Olsder [17], if the equilibrium strategy profile is deterministic, a pure strategy Nash equilibrium exists. For finite games, even if a pure strategy Nash equilibrium does not exist, a mixed strategy Nash equilibrium can be found. Nash equilibrium point corresponds to the steady-state of the game and is predicted as the most probable outcome of the game [18].

The proposed model is of the form of a potential game. It can be shown that there exists a function known as the potential function $V: S \rightarrow \mathfrak{R}$, that reflects the change in utility value accrued by unilaterally deviating player [19]. Any potential game in which players take actions sequentially converges to a pure strategy Nash Equilibrium that maximizes the potential function regardless of the order of play and the initial condition of the game [19]. The utility function of the proposed game model is given as: [13]

$$U_i(p, q) = \sum_{k=1}^M [p_{ik} \cdot D_{ik}] = \sum_{k=1}^M \left[\begin{aligned} & a_k \cdot c_i + a_k \cdot k_i \cdot \sum_{l=1}^M a_l - a_k \cdot k_i \cdot \sum_{l=1}^M b_l \cdot p_{il} + a_k \cdot k_i \cdot \sum_{l=1}^M \sum_{j=1, i \neq j}^N t_{jl} \cdot p_{jl} + a_k \cdot w_{ik} \cdot q_{ik} \\ & - a_k \cdot \sum_{j=1}^N w_{jk} \cdot q_{jk} - c_i \cdot b_k \cdot p_{ik} - b_k \cdot p_{ik} \cdot k_i \cdot \sum_{l=1}^M a_l + b_k \cdot p_{ik} \cdot k_i \cdot \sum_{l=1}^M b_l \cdot p_{il} \\ & - b_k \cdot p_{ik} \cdot k_i \cdot \sum_{l=1}^M \sum_{j=1, i \neq j}^N t_{jl} \cdot p_{jl} - b_k \cdot p_{ik} \cdot w_{ik} \cdot q_{ik} + b_k \cdot p_{ik} \cdot \sum_{j=1, i \neq j}^N w_{jk} \cdot q_{jk} + c_i \cdot \sum_{j=1, i \neq j}^N t_{jk} \cdot p_{jk} \\ & + k_i \cdot \sum_k a_k \cdot \sum_{j=1, i \neq j}^N t_{jk} \cdot p_{jk} - k_i \cdot \sum_k b_k \cdot p_{ik} \cdot \sum_{j=1, i \neq j}^N t_{jk} \cdot p_{jk} + k_i \cdot \sum_k \left(\sum_{j=1, i \neq j}^N t_{jk} \cdot p_{jk} \right)^2 \\ & + w_{ik} \cdot q_{ik} \cdot \sum_{j=1, i \neq j}^N t_{jk} \cdot p_{jk} - \sum_{j=1, i \neq j}^N w_{jk} \cdot q_{jk} \cdot \sum_{j=1, i \neq j}^N t_{jk} \cdot p_{jk} \end{aligned} \right] \quad (9)$$

The following partial derivatives are calculated using the above given utility function: [13]

$$\frac{\partial^2 U_i}{\partial p_{ik} \partial p_{jk}} = \sum_{j=1, i \neq j}^N t_{jk} \quad \text{and} \quad \frac{\partial^2 U_j}{\partial p_{ik} \partial p_{jk}} = \sum_{i=1, i \neq j}^N t_{ik} \quad (10)$$

where t_{jk} represent effect of price variations of i^{th} service provider's competitors on i^{th} service provider's demand. Since a customer is equally influenced from service providers' price variations: [13]

$$\sum_{j=1, i \neq j}^N t_{jk} = \sum_{i=1, i \neq j}^N t_{ik} \quad (11)$$

Hence,

$$\frac{\partial^2 U_i}{\partial p_{ik} \partial p_{jk}} = \frac{\partial^2 U_j}{\partial p_{ik} \partial p_{jk}} \quad i \in \{1, \dots, N\}; k \in \{1, \dots, M\} \quad (12)$$

The exact potential function for the proposed game is given as: [13]

$$V(p, q) = \sum_{i=1}^N \sum_{k=1}^M \left[\begin{aligned} & -a_k \cdot k_i \cdot \sum_{l=1}^M b_l \cdot p_{il} - c_i \cdot b_k \cdot p_{ik} - b_k \cdot p_{ik} \cdot k_i \cdot \sum_{l=1}^M a_l + b_k \cdot p_{ik} \cdot k_i \cdot \sum_{l=1}^M b_l \cdot p_{il} \\ & - b_k \cdot p_{ik} \cdot k_i \cdot \sum_{l=1}^M \sum_{j=1}^N t_{jl} \cdot p_{jl} - b_k \cdot p_{ik} \cdot w_{ik} \cdot q_{ik} + b_k \cdot p_{ik} \cdot \sum_{j=1}^N w_{jk} \cdot q_{jk} - k_i \cdot \sum_{l=1}^M b_l \cdot p_{il} \cdot \sum_{j=1}^N t_{jk} \cdot p_{jk} \end{aligned} \right] \quad (13)$$

5 Case Study

A demonstrative example where two intelligent transportation system service providers are competing in the same market is constructed to evaluate the applicability of the proposed framework.

In the constructed game, the players are trying to maximize their potential function, but it is assumed that they take turns one at a time in a round-robin fashion to change the price of their offerings. In each step, the algorithm calculates the price value for a service provider that maximizes its potential function. For the calculation the most recent price decisions of other players in the previous step is

used. The related algorithm is summarized as follows: [13]

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define t = time step; t = 0;
{ set initial price value for each service provider;
t = t + 1;
while p*(t) - p*(t-1) > ε
{ t = t + 1;
for i=1 to N
{ pick ith service provider;
given the price values of competitors, find
pik* = argmax (V) of ith service provider; }
end; }
    
```

The parameters used in the calculations are given in Table 1. SP denotes the service providers, C denotes the customers. Table 1 models a typical customer's sensitivity to the quality and prices of the services offered by the service providers given the quality and price of the competitors.

Table 1. Case Study Parameters

	SP ₁		SP ₂			SP ₁	SP ₂
	C ₁	C ₂	C ₁	C ₂			
w _{ik}	0.60	0.30	0.20	0.10	c_i	2	2
w _{jk}	0.05	0.05	0.10	0.10	q_i	0.75	0.6
t _{jk}	0.03	0.08	0.10	0.15	k_i	0.20	0.15
t _{1ik}	0.50	0.50	0.50	0.50			
t _{2ik}	0.50	0.50	0.50	0.50			
b _k	0.10	0.30	0.10	0.30			
a _k	20	20	20	20			
TF _k	1	1	1	1			
LF _k	0.75	0.75	0.75	0.75			

In the case study two customer profiles are created: a high profile customer (C₁) and a low profile customer (C₂). The base demand (a) is assumed the same for both customer profiles and is set at 20 for each. The base demand represents average demand of different customer profiles.

Similar to customer profiles, service providers are also differentiated in their preferences. The first service provider (SP₁) attaches more importance to its QoS level, compared to second service provider (SP₂). It also pays much attention to the QoS levels of its opponent when calculating service prices. The corresponding values for customers are set according to their quality sensitivities. The service providers are assumed to have same fixed costs (c_i). t_{1ik} and t_{2ik} parameters are all set equal to 0.5 for the sake of simplicity [13]. They should reflect the marketing preferences of service providers. The results of the algorithm at the equilibrium point is summarized in Table 2.

Table 2. Results At The Equilibrium

	SP ₁		SP ₂	
	C ₁	C ₂	C ₁	C ₂
p*	9.991	9.766	7.781	7.721
Demand	19.779	18.228	19.522	18.465
Utility	375.643		294.450	

Analyzing to the results, it can be observed that SP₁ will maximize its utility when it sets its prices 9.978 and 9.753 to the first and second customer accordingly. The resulting demand is calculated as

19.783 and 18.234. Both service providers are able to sell more services to the high profile customer with higher prices. As the second customer is more price conscious, it demands more from the second service provider. The opposite is also observable, as the high profile customer prefers the high priced service provider. When the strategies of service providers are compared, the effect of QoS level on the service price is enabling the first service provider to set its prices higher than its competition. Hence, the second service provider in order to maximize its utility has to set a lower price level than its competitor.

6 Conclusion

Intelligent transportation systems typically require high amount of investment. Therefore, mechanisms that will contribute to the utilities of service providers are of great importance for market acceptance and effective deployment. Classic usage-based pricing mechanisms are usually too static to handle fluctuating demand and resource constraints expected in sensor based infrastructures. Pricing models related to time, related to demand or related to sensitivity/loyalty have more potential to respond to more demanding and price and quality sensitive customers.

Though, finding the right price for different customers requires that their buying habits, their sensitivities are identified. This process requires extensive data mining, which should produce the data needed to create efficient algorithms for pricing and setting the correct levels of quality.

In the proposed game theoretical model, the service providers in the marketplace are defined as players that try to optimize a joint objective function, the potential function. The model calculates the price depending on the QoS level of a service provider and its competitors. The demand function chosen in the model also takes into account the prices offered by other service providers in the market. The outcome of the game is the optimum prices of the services given corresponding QoS levels. The simulation results reveal that the prices offered to customers depend on the QoS level of the service as well as on the prices and QoS levels offered by the customers.

Future work could create more realistic scenarios where prices of services are accepted with different probability levels depending on customer profiles. This addition could prove more effective in a more dynamic setting as expected in IoT environments.

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