Smart Data Pricing Model for Intelligent Transportation Systems

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***Abstract*- Internet of Things is a novel paradigm that foresees Internet-connected devices generating constantly new data using sensors/actuators. The gathered data from various sources facilitates new ways of integration and operations that are essential for developing systems, such as intelligent transportation management. Intelligently managing an infrastructure like traffic systems is expected to contribute to overall safety, economical development and environmental sustainability. However, its success depends on users' willingness to share with and use data provided by the platform. Therefore, there should be mechanisms to be put in place, which will motivate latent customers/contributors and furthermore manage efficiently the flow of data on possibly stringent network conditions. Smart data pricing, a concept that aims to give users the right economic incentives and manage network congestion in high demand periods, is providing an effective solution for this problem. In this paper, models based on game theory is used to deal with data pricing. The applied model takes into account the level of service quality and the sensitivity of the customers on price levels and quality. The applicability of the proposed methodology is demonstrated via a case study.**

Keywords- Internet of Things; dynamic pricing; game theory; mobile cloud computing.

I. INTRODUCTION

The Internet of Things (IoT), a revolutionizing approach foreseeing "smart, connected" products is promising its early adaptors new competitive opportunities and is seen as a disruptive technology [1]. There are several prominent organizations, such as Google, General Electric, Amazon, Samsung, etc. coming with their own view of the concept. It is basically a new model that has its roots based on ever advancing wireless communications along with the artificial intelligence framework that is expected to enhance the experience of the users. From the end users' perspective, the whole experience of IoT should contribute especially in areas of assisted living, e-health, enhanced learning and from the business users' perspective in fields, such as automation, industrial manufacturing, logistics, business/process management, intelligent transportation of people and goods [2].

As it is with every newly emerging technology, the IoT vision requires that organizations should develop beyond traditional mobile computing scenarios and propose products that should connect everyday existing objects and embed somehow intelligence into their offerings [3]. As proposed by [3], IoT demands: (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. If the organizations are able to deliver in all these aspects the desired smart connectivity and context-aware computation should be the outcome.

Intelligent transportation systems enriched with IoT as suggested by Ibanez et al. [4] aim to achieve goals, such as safety and personal security, access and mobility, environmental sustainability, and economical development through minimizing CO2 emissions, improving traffic efficiency, and road safety, as well as reducing vehicle wear, transportation times and fuel consumption. However, developing such a framework necessitates integration of information and communication technologies that are usually treated as independent silos of automation. Prospects of possible integration anticipates large amount of data to be collected, processed and fed back on real-time if possible to the users' of the system. The main challenge for the adaptation of intelligent transportation systems is in the implementation of adequate and necessary technologies and infrastructures in vehicles, roads, streets and avenues [4].

However, new business opportunities created through processed information and delivered as a service to customers, may establish new revenue streams for service providers [5]. Effectively managing information and keeping quality of service levels under control in case of constrained network conditions necessitates new approaches, such as smart data pricing. Smart data pricing, a mechanism aiming to understand users' behaviors and adapting to different network traffic conditions is believed to be a solution for creating economic models for computing optimized prices [6]. Accordingly, service providers will have to develop economic models for price competition that should adapt to customers' expectations and network conditions.

In this work, an economic model for price competition among service provider in transportation networks is proposed. The model aims to analyze consumers' behaviors

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to changing prices and quality levels and tries to optimize service providers' revenues. The proposed framework is based on mathematical models of game theory.

The case study used to demonstrate the effectiveness of proposed methodology defines different scenarios. The aim is to examine the effect of different behaviors on the pricing and depict actions that should maximize revenue of the service providers.

The remaining part of the paper is organized as follows: in Section 2 related literature is given. Section 3 briefly describes the methodologies that constitute the proposed framework. The steps and details of the implementation into the intelligent transportation management problem is given in Section 4. Finally, Section 5 concludes the study.

II. LITERATURE REVIEW

Internet of Things related literature covers different aspects of the topic, ranging from enabling technologies to protocols and possible application scenarios. Similarly, intelligent transportation systems related problems and propositions are very popular among research community. Some of the recent work that constituted the base of this study is presented in this section.

In their work, Ibáñez et al. [4] presented emerging technologies, such as connected vehicles, wireless technologies, etc. that will complement intelligent transportation systems. They showed using examples how cloud computing complements the development of transportation systems. They also discussed how IoT will contribute to seamless integration of different systems with the intention of more sustainable transportation solutions and improved road safety.

Niyato et al. [7] introduced an overview of IoT, its architecture, benefits and business models and proposed smart data pricing for IoT systems and services. They suggested a pricing scheme for IoT service providers taking into account sensing data buying and service subscription with bundling. They found out that in case of a coalition, multiple service providers could achieve a higher profit level.

Hoang and Niyato [5] developed an economic model for competitive pricing problem among information service providers in an Internet-of-Vehicle environment. They proposed a competitive repetitive game model to obtain prices for providers through Nash equilibrium solution. Using simulation results, they assessed the efficiency of their solution.

Sen et al. [6] proposed smart data pricing mechanisms to avoid network congestion by creating incentives to modify user behavior or shift demand to less congested times or to supplementary networks. They discussed two different scenarios: time-dependent pricing and traffic offloading and foreseen smart data pricing applied to machine-to-machine communication and IoT setting.

III. THE METHODOLOGY

Smart data pricing concept describes pricing options applied by service providers to replace traditional flat-rate model. Typical models make use of mechanisms, 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 [6]. Dynamic pricing approach as part of smart data pricing enables real-time pricing changes and ability to respond to network congestion and fluctuations in quality of experience of the users' of the system.

However, setting prices without considering the reactions of competition possibly underoptimizes the market share and utilities of service providers. However, answering questions like: "How can we decide what action to choose in a competitive environment?" and "What are other companies doing?" requires study of market conditions and behaviors of actors in the market [8].

Game theory defined as the formal study of conflict and cooperation provides a language to formulate, structure, analyze and understand strategic scenarios [9]. Game theory framework consists of theoretical methods of microeconomic origin and are used in many other areas of the economy and in a range of other social and behavioral sciences [10].

The basic requirements for establishing a game theoretical model necessitates definition of players, their preferences, their information, strategic actions available to them, and how they influence the outcome. At this point whether or not the players have the inclination or possibility of cooperation should also be defined.

There are several assumptions made at this stage and one of the most common one is that players are considered as rational. A rational player is defined as the one who always chooses an action that gives the result that is most preferred considering the expected reactions of its opponents.

The approach applied in this paper assumes non-cooperative games with rational actors. In game theory, typically solution approaches are based on Nash equilibrium concept, which is used to analyze the outcome of the strategic interaction of several decision makers. The Nash equilibrium tries to predict what will happen if several persons or institutions are making decisions at the same time, and if the result depends on the decisions of others. After having chosen strategies, no player should benefit by reconsidering his strategy while the other players keep all their strategies unchanged. If this is the case, the current set of strategic choices and corresponding utilities represent Nash equilibrium.

IV. DATA PRICING FRAMEWORK

A. *Proposed Model*

The game theoretical framework used in this paper is based on researches of Işıklar Alptekin and Bener [11] [12] and Demirci and Alptekin [13], who applied the same framework to revenue management in e-commerce. In their work Işıklar Alptekin and Bener [11] [12] considered short term sub-lease of unutilized spectrum bands to different service providers using a non-cooperative game theoretical model. As outcome of the game, they calculated the optimum prices of the offered frequency bands subject to QoS constraints. They concluded that the demand models must be chosen with great care, since the choice of its parameters has profound implications for the market equilibrium. Based on their research, the pricing problem for intelligent transportation system is formed as follows:

Players: data based service provider in intelligent transportation network

Actions and strategies: The choice of the price offering based on quality of experience levels

The main assumption of the model is service providers are competing with each other non-cooperatively and independently. The possible actions are defined as: the price of the service provided along with its quality level. The decision of the service providers and also the consumers are affected by the action of other service providers. The aim for the providers is typically profit maximization.

As mentioned in the previous section, game theoretical models are in search of a focal point, from which no player would deviate, i.e., a Nash equilibrium.

The pricing strategy set consists of a set of N service providers, SP_i, designated by $i = \{1,2, ..., N\}$. Each company has to define two sets of parameters: $(p, q) \in \mathcal{R}_{+}^{2N}$. $\boldsymbol{p} = \{\boldsymbol{p_{1k}}, \boldsymbol{p_2}, \dots, \boldsymbol{p_{Nk}}\}$ is the price vector and p_{ik} is the price that SP_i charges for each service provided to k^{th} customer. The prices may be based on cloud resources used or value-added data services provided. $\boldsymbol{q} = \{\boldsymbol{q_{1k}}, \boldsymbol{q_{2k}}, \dots, \boldsymbol{q_{Nk}}\}$, is the experienced quality level of the services, where q_{ik} measures the quality offered by SP_i to k^{th} customer.

The demand for each service provider is represented with $D_i(p,q)$: $\mathcal{R}_{+}^{2N} \rightarrow \mathcal{R}_{+}$. The model assumes that the demand of SP_i depends not only on its own parameters p_i and q_i, but also on the prices and quality level offered by its competitors. The utility function is defined as $U_{ik}(p,q)$: $\mathcal{R}_{+}^{2N} \rightarrow \mathcal{R}_{+}$. The strategy space of $S_{ik} \in \mathcal{R}^2$ is defined as the subset of : [11]

$$S_{ik} = \left\{(p_{ik}, q_{ik}): 0 \le p_{ik}^{min} \le p_{ik} \le p_{ik}^{max} \,;\, 0 \le q_{ik}^{min} \le q_{ik} \le q_{ik}^{max}\right\} \quad (1)$$

As suggested by [11] beyond some maximum price, demand will be zero whatever the prices and QoS levels of competitors are. Accordingly, the service provider has to define an upper bound on price. The lower bound is set so as to keep the net profit of the *SP* positive.

In this model, we assume that the average demand is linear in prices and thus given as a linear demand function in the following form [11]:

$$D_{ik}(p,q) = a_{ik} - b_{ik}.p_{ik} + \sum_{j \in I, j \neq i} c_{ijkl}.p_{jk} + \beta_{ik}.q_{ik} - \sum_{j \in I, j \neq i} \gamma_{ijkl}.q_{jk} \ge 0 \quad (2)$$

with a_{ik} defined as the base demand of k^{th} customer from i^{th} service provider and $b_{ik}, c_{ijkl}, \beta_{ik}, \gamma_{ijkl}$ are positive constants representing the extent to which customers are affected by changes in the price and quality. c_{ijkl} is the measure that shows how the l^{th} customer is influenced by the price of SP_i to the k^{th} costumer when l^{th} customer is served by SP_k. The constants b and c should satisfy the following condition:

$$b_{ik} > \sum_{j \neq i} c_{ijkl}, i, j \in I \text{ and } k, l \in I \quad (3)$$

The condition requires that the influence of a service providers' own price is larger on its own demand than the prices of its competitors. This is the typical scenario under the assumptions of loyalty or the imperfect knowledge of competitors' prices.

The demand function defined in the model assumes that the customers are aware of the service quality they are receiving and therefore are sensitive to quality changes. The parameters reflecting the sensibility to experienced quality levels are defined with parameters q_i and q_j, respectively. An objective calculation of the quality parameters should include service related performance metrics, such as bandwidth, response times, and resources dedicated to user, etc. In this paper, an experienced service level will be used for demonstration purposes.

Having defined the quality related parameters, the revenue of a service provider is calculated by multiplying its price with its demand:

$$U_i(p,q) = p_i.D_i(p,q) \quad (4)$$

When the demand function is replaced with the equation 2:

$$U_i\,(p,q) = p_i\,(a_{ik} - b_{ik}.p_{ik} + \sum_{j \in I, j \neq i} c_{ijkl}.p_{jk} + \beta_{ik}.q_{ik} - \sum_{j \in I, j \neq i} \gamma_{ijkl}.q_{jk} \quad (5)$$

At this stage, the existence and uniqueness of the equilibrium among service providers has to be proven.

As defined by [11], a single-parameter Nash equilibrium in p at q is the vector p^* that solves for all i:

$$U_i(p^*, q) = \max_{p_{ik}, q \in \mathcal{R}_i} U_i\left(p_{1k}^*, \cdots, p_{(i-1)k}^*, p_{ik}^*, p_{(i+1)k}^*, p_{Nk}^*, q\right) \quad (6)$$

In order to prove the Nash equilibrium the supermodularity of the game has be to shown. Supermodular games require that when a player takes additional actions, others want to do the same. The game G is defined to be supermodular if the following conditions are met [11]:

S_n is an interval of $\mathcal{R}^N$, where

$$S_n = \left[\underline{y_n}, \overline{y_n}\right] = \left\{x \middle| \underline{y_n} \le x \le \overline{y_n}\right\} \quad (7)$$

f_n is twice continuously differentiable on S_n ;

$\frac{\partial^2 f_n}{\partial x_{ni} \partial x_{mj}} \ge 0$ for all n and all $1 \le i < j \le N$;

$\frac{\partial^2 f_n}{\partial x_{ni} \partial x_{mj}} \ge 0$ for all $n \neq m$, $1 \le i \le N$ and $1 \le j \le M$.

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A pure Nash equilibrium is a strategy tuple $x = (x_n; n \in N)$, such that each x_n maximise $f(\hat{x}_n, x_{-n})$ over S_n. The strategic feasible set of the game is defined using the following formulation [11]:

$$S_i = \{p_i: 0 \leq p^{min} \leq p_i \leq p^{max}; i = 1,2, \dots, N\} \quad (8)$$

The partial derivatives of the utility function for prices and quality levels are calculated and given as:

$$\frac{\partial U_i(p,q)}{\partial p_i} = D_i(p,q) - b_i.p_i \quad (9)$$

$$\frac{\partial^2 U_i(p,q)}{\partial p_i^2} = -2b_i \leq 0 \quad (10)$$

$$\frac{\partial U_i(p,q)}{\partial q_i} = \beta_i.p_i \quad (11)$$

$$\frac{\partial^2 U_i(p,q)}{\partial q_i^2} = 0 \leq 0 \quad (12)$$

$$\frac{\partial^2 U_i(p,q)}{\partial p_i \partial p_j} = \sum_{i \neq j} c_{ij} \geq 0 \quad (13)$$

In order to find the prices that maximizes revenue, the derivative of the utility function is taken and set equal to zero:

$$\frac{\partial U_i\,(p,q)}{\partial p_i} = D_i(p,q) + p_i(-b_i) = 0 \quad (14)$$

$$\frac{\partial U_i\,(p,q)}{\partial p_i} = a_i - b_i.p_i + \sum_{j \in I, j \neq i} c_{ij}.p_j + \beta_i.q_i - \sum_{j \in I, j \neq i} \gamma_{ij}.q_j - b_i.p_i = 0 \quad (15)$$

$$\frac{\partial U_i\,(p,q)}{\partial p_i} = a_i - 2.b_i.p_i + \sum_{j \in I, j \neq i} c_{ij}.p_j + \beta_i.q_i - \sum_{j \in I, j \neq i} \gamma_{ij}.q_j = 0 \quad (16)$$

$$2.b_i.p_i - \sum_{j \in I, j \neq i} c_{ij}.p_j = a_i + \beta_i.q_i - \sum_{j \in I, j \neq i} \gamma_{ij}.q_j \quad (17)$$

As a linear system of equation in p, the equations can be represented in a matrix form.

$$Ap = \left[a_i + \beta_i.q_i - \sum_{j \in I, j \neq i} \gamma_{ij}.q_j\right] \quad (18)$$

$$A = \begin{pmatrix} 2b_1 & -c_{12} \cdots & -c_{1N} \\ -c_{(N-1)1} \vdots & \ddots & -c_{(N-1)N} \vdots \\ -c_{N1} & -c_{N2} \cdots & 2b_N \end{pmatrix} = \Phi(1-T) \quad (19)$$

$$\Phi = diag(2b_1, 2b_2, \dots, 2b_N) \quad (20)$$

$$T = \begin{pmatrix} 0 & \cdots & \frac{c_{1N}}{2b_1} \\ \vdots & \ddots & \vdots \\ \frac{c_{N1}}{2b_N} & \cdots & 0 \end{pmatrix} \quad (21)$$

Hence, $A^{-1} = (I-T)^{-1}.\Phi^{-1}$ and optimum price at the equilibrium is defined as:

$$p^* = A^{-1}.X = (I-T)^{-1}.\Phi^{-1}.X \quad (22)$$

with

$$X = a_i + \beta_i.q_i - \sum_{j \in I, j \neq i} \gamma_{ij}.q_j \quad (23)$$

$$p_i^* = \sum_{j=1}^{N} A_{ij}^{-1}.a_i + (A_{ii}^{-1}.\beta_i - \sum_{i \neq j} A_{ij}^{-1}.\gamma_{ji}).q_i + \sum_{j \neq i}(A_{ij}^{-1}.\beta_j - \sum_{l \neq j} A_{il}^{-1}.\gamma_{li}).q_j \quad (24)$$

The contraction approach that proves the uniqueness of the equilibrium defines the sufficient condition as below [11]:

$$\frac{\partial^2 U_i(p,q)}{\partial p_i^2} + \sum_{i \neq j} \left|\frac{\partial^2 U_i(p,q)}{\partial p_i \partial p_j}\right| < 0 \quad (25)$$

$$-2b_i + \sum_{i \neq j} c_{ij} < 0 \quad (26)$$

Therefore, if the conditions are met, the equation 24 will result in the optimum prices for SP_i.

B. Numerical Application

The applicability of the proposed model is demonstrated through a demonstrative example where two intelligent transportation system service providers with different experienced quality levels are competing in the same market.

The perceived quality levels along with the parameters used in the calculations are given in Table 1. *NP* denotes the service providers, *C* denotes the customers.

The parameters defined in Table 1 try to model 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. Solving the formula given in 24, the Nash equilibrium price is p^* obtained.

TABLE I. THE VALUES OF THE PARAMETERS OF THE DEMAND FUNCTION

	NP_1		NP_2	
	C_1	C_2	C_1	C_2
β	4.5	4.5	3	3
$\gamma_{NP_1 \to C_1}$	0	1.5	0.8	0.5
$\gamma_{NP_2 \to C_1}$	1.5	0	0.5	0.8
$\gamma_{NP_1 \to C_2}$	1.3	1.4	0	1.1
$\gamma_{NP_2 \to C_2}$	1.4	1.3	1.1	0
b	4.5	4.5	7	7
$c_{NP_1 \to C_1}$	0	1.5	2.2	1.9
$c_{NP_2 \to C_1}$	1.5	0	1.9	2.2
$c_{NP_1 \to C_2}$	1.1	1.6	0	1.5
$c_{NP_2 \to C_2}$	1.6	1.1	1.5	0
q	0.75	0.75	0.85	0.85

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For demonstrative purposes, the parameters used in the case study assume two customer profiles: a high profile customer (C_1) and a low profile customer (C_2). The base demand (a) is assumed to be the same for both customer profiles and is set at 20 for each. The base demand represents average demand of different customer profiles.

The following matrix is used to calculate the values of demand (D), the price (p^*), and the utility (U^*).

$$\boldsymbol{A} = \begin{pmatrix} 9 & -1.5 & -1.1 & -1.6 \\ -1.5 & 9 & -1.6 & -1.1 \\ -2.2 & -1.9 & 14 & -1.5 \\ -1.9 & -2.2 & -1.5 & 14 \end{pmatrix}$$

The formula given in 24 is used to obtain the results presented in Table 2.

TABLE II. OPTIMUM RESULTS FOR PRICE, DEMAND AND UTILITY

	$\boldsymbol{NP_1 \to C_1}$	$\boldsymbol{NP_2 \to C_1}$	$\boldsymbol{NP_1 \to C_2}$	$\boldsymbol{NP_2 \to C_2}$
$\boldsymbol{D}$	16.65	16.90	19.94	20.12
$\boldsymbol{p^*}$	3.70	3.76	2.85	2.87
$\boldsymbol{U^*}$	61.62	63.53	56.80	57.83

The effect of the changes in experienced quality level is shown in Table 3, where the quality level of the first service provider is increased to %100 and the quality level of the second service provider is decreased to 1%.

TABLE III. OPTIMUM RESULTS WITH THE CHANGE OF QUALITY LEVEL OF THE FIRST SERVICE PROVIDER

	$\boldsymbol{NP_1 \to C_1}$	$\boldsymbol{NP_2 \to C_1}$	$\boldsymbol{NP_1 \to C_2}$	$\boldsymbol{NP_2 \to C_2}$
$\boldsymbol{D}$	17.96	15.43	20.77	18.99
$\boldsymbol{p^*}$	3.99	3.43	2.97	2.71
$\boldsymbol{U^*}$	71.68	52.88	61.65	51.57

When the sensitivity for quality of the low profile customer is set as high profile customer, the following optimum results are obtained (Table 4).

TABLE IV. OPTIMUM RESULTS AFTER VARIATION OF THE SENSITIVITY FOR QUALITY OF THE LOW PROFILE CUSTOMER

	$\boldsymbol{NP_1 \to C_1}$	$\boldsymbol{NP_2 \to C_1}$	$\boldsymbol{NP_1 \to C_2}$	$\boldsymbol{NP_2 \to C_2}$
$\boldsymbol{D}$	16.83	17.08	20.67	20.92
$\boldsymbol{p^*}$	3.74	3.80	2.95	2.99
$\boldsymbol{U^*}$	62.94	64.85	61.03	62.49

In the opposite case where high profile customer is no longer sensitive to the quality, the following optimum results are obtained (Table 5).

The results of demonstrative examples show that demand and accordingly prices are changing when different sensibility values for quality are used. However, in real life scenarios setting the correct values for quality and price sensibility to different customers requires that their profile should be extracted from the relationship between customer and service providers using techniques, such as customer relationship management, big data analysis, etc. If correct profiles could be identified, the resulting pricing mechanism and hence the prices will be realistic.

TABLE V. OPTIMUM RESULTS AFTER VARIATION OF THE SENSITIVITY FOR QUALITY OF THE HIGH PROFILE CUSTOMER

	$F_1 \to A_1$	$F_2 \to A_1$	$F_1 \to A_2$	$F_2 \to A_2$
D	14.30	14.36	18.69	18.87
p^*	3.18	3.19	2.67	2.69
U^*	45.43	45.84	49.92	50.85

When the results presented in tables are analyzed, several conclusion could be drawn. For example, Table 3 reveals that demand of high profile customers to the first service provider has increased and the demand of the same customer to the second service provider has decreased, when the quality level of the first provider is increased and the second provider is decreased. Moreover, the price of the first service provider is increased for all customer profiles. Hence, the first service provider with its increased experienced quality level is able to increase its total utility, whereas the second service provider with its decreased utility potentially also lost revenue.

The effect of sensitivity levels of customer profiles is explored in Table 4 and Table 5. Here, the most striking finding is when a customer sacrifices his/her desire for quality, prices are falling. On the other hand, if all customers are becoming more sensitive to the quality, prices are increasing. Final finding is that the revenues of the service providers are increasing when all customers demand for a higher experienced level of quality and also accept paying more money.

V. CONCLUSION

Intelligent transportation systems with their expected benefits will shape the future traffic flow and contribute to sustainability of the communities and will be a potential life saver in cases of accident prevention. The proposed methodology in this paper aims to approach the intelligent transportation system from the service providers' perspective. As the system requires high amount of investment, pricing mechanisms that will contribute to the utilities of service providers and also manage the quality levels experienced by the system's customers are of great importance. Simple usage-based pricing mechanisms will be potentially infective under these circumstances. Pricing models related to time, related to demand or related to sensitivity/loyalty have the ability to respond to ever increasing awareness of customers of prices and quality levels in the marketplace.

However, setting the right price for different consumer profiles requires that the market properties are well captured. Especially, in order to know the customers, all necessary data about their buying habits, their sensitivity on certain factors and what they seek in the market should be explored meticulously. 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.

Future work could explore more realistic scenarios where prices of services are accepted with different possibility levels by different customer profiles, which should reveal the dynamic structure of pricing mechanism better.

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