Adaptive Dynamic Pricing for Market-based Allocation of Interdependent Commodities

Doctoral Consortium

Jan Mrkos
Artificial Intelligence Center, Faculty of Electrical Engineering, Czech Technical University in Prague
Prague, Czech Republic
mrkos@agents.fel.cvut.cz

ABSTRACT

Ongoing digitization of all kinds of human enterprise is allowing sophisticated pricing strategies to be used in domains where previously this has not been feasible. In the mobility domain, commodities such as shared cars or electric vehicle charging services have multiple free parameters that determine their utility to customers. Additionally, sales of individual service items are interdependent, meaning each sale of a service items impacts all consecutive sales. In this thesis, our goal is to concisely describe structure of these commodities and to develop pricing algorithms that improve revenue of service providers and the quality of allocations of these commodities. To this end, we describe the *interdependent commodities multi-agent pricing problem model* and develop markov decision process based pricing strategy that improves both service provider revenue and resource utilization in the electric vehicle charging domain.

KEYWORDS

Dynamic Pricing, Markov Decision Process, Innovative agents and multiagent applications, EV charging, Electric vehicle, Resource Allocation

ACM Reference Format:
Jan Mrkos. 2018. Adaptive Dynamic Pricing for Market-based Allocation of Interdependent Commodities. In *Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), Stockholm, Sweden, July 10–15, 2018,* IFAAMAS, 3 pages.

1 DYNAMIC PRICING OF INTERDEPENDENT COMMODITIES

Dynamic pricing is a pricing strategy in which the seller determines the price of its product dynamically, as opposed to setting a fixed price. The price adjustments can happen at regular intervals or at some non-regular prompt. Dynamic pricing has been studied in multiple scientific fields [3, 8] and can be applied in various markets in many forms, such as the end-user energy market [1], sales of airline tickets [2, 7], hotel bookings[5] and recently also electric vehicle charging services[10].

Digital technology has made it possible for business to use dynamic pricing in circumstances where this was previously not feasible. Digitization provides means of adjusting prices easily as well as means for disseminating the price information to consumers and also to collect data needed for pricing optimization.

In this work, we focus on the dynamic pricing strategy for perishable interdependent structured commodities with multiple free parameters. By structured interdependent commodities we mean non-uniform commodities that consist of interdependent parts that can have number of free parameters. Example of such comoddities are electric vehicle (EV) charging services or shared vehicles.

Defined by multiple parameters, each commodity (existing in possibly continuousproduct parameter space) is unique and varying the parameters of the commodity can significantly change its utility to the customer. For example, price, charging rate, and time of charging define the EV charging process and changing any of these parameters can deter user from purchasing the service.

Furthermore, these commodities are interdependent, meaning that sale of one can impact all following sales. For example, sale of one charging session can block other charging sessions in time as well as through reduced grid capacity.

To allocate these commodities efficiently, we need to define ways of efficiently describing and pricing them.

2 THESIS GOALS

In this thesis, we aim to explore consise ways of describing interdependent commodities and how to price these commodities in different environmental settings.

Research goals for this doctoral thesis are thus following:

(1) Develop a *formal method for describing structured commodities* and encoding their properties in the models of environment.
(2) Devise *set of algorithms for dynamic pricing* of structured commodities that naturally operate with their structure.
(3) Experimentally *evaluate these algorithms in realistic domains* with primary focus on the mobility domain and determine the effect of the environmental parameters on the choice of pricing algorithm.

Primary use cases for our dynamic pricing strategy are in the mobility domain. Allocation of charging resources to EV drivers and allocation of vehicles in car-sharing are examples of domains we focus on. Both EV charging resources and shared cars are structured commodities in a sense that each commodity has different geographical location, varying availability and varying quality of service.

With dynamic pricing we focus on developing a pricing strategy for a seller in established market and not on the design of the

Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), M. Dastani, G. Sukthankar, E. André, S. Koenig (eds.), July 10–15, 2018, Stockholm, Sweden.

market. Nor do we consider optimization of the commodities themselves, such as optimization of the charging station placement[9]. Currently, we do not consider the competitive aspects of the problem, neither on supply side[10], nor on demand side (such as [4]). However, we would like to extend this work to the game-theoretic setting in the future.

We expect the environment to determine to some degree the complexity of the pricing strategy. We want to explore this relationship in our work. To give an example, in the EV charging domain, complex dynamic pricing strategy that permits reservations might not be welcomed by the drivers if the environment contains a lot more available charging stations than drivers.

We want to employ large agent based simulations to evaluate our pricing strategy algorithms in different environmental settings. Using simulator based on the AgentPolis [6], we can evaluate different pricing strategies in different settings with relative ease.

3 INTERDEPENDENT COMMODITIES PRICING PROBLEM MODEL

Currently we model the pricing problem as multiagent system with n customer agents and single service provider.The model is formally defined as tuple $M = \langle D, c, \phi_1, \ldots, \phi_n, \Phi \rangle$. $D = (r_1, \ldots, r_n)$ is a demand expressed as a sequence of *service requests* r_i sent by the customer agents to the service provider agent in a sequence. Each service request r_i contains parameters of the service based on which the service providers *pricing strategy* Φ determines the price $p_i = \Phi(r_i)$. The pricing strategy is subject to capacity constraints c. Customers *decision processes* $\phi_1, \ldots, \phi_n$ determine the customers decision $\phi_i(p_i)$, which is either to accept the offered price or reject it.

An execution of the model is a sequence of prices and decisions $(\langle p_1, \phi_1(p_1) \rangle, \ldots, \langle p_n, \phi_n(p_n) \rangle)$ for all agents and their charging requests r_i. The goal of the service provider is to maximize its revenue by optimally setting prices with Φ:

$$\Phi^* = \arg\max_{\Phi} \rho(D, c, \phi_1, \ldots, \phi_n, \Phi). \quad (1)$$

The maximization task is subject to the capacity constraints c that need not be static.

4 MDP BASED DYNAMIC PRICING STRATEGY

We developed dynamic pricing strategy that provides pricing strategy Φ for the model described above.

This dynamic pricing strategy maximizes revenue of the service provider by using Markov Decision Processes (MDPs) to determine price. In our current version of pricing strategy, we partition the pricing period into time slots. In each time slot, we use one MDP to determine the price. States in each MDP are are determined by the triplet of *time to the service realization, price level* and *capacity level.* Possible actions are to increase or reduce price. *Expected demand* is incorporated in the MDP naturally through the structure of the MDPs transition function.

Finding optimal pricing for full problem 1 is difficult as the state space can become very large. Splitting the full problem into independent time windows allows us to find tractable solutions. However, these solutions are only a bound to the optimal solutions to the full problem. In future version of the method, we plan to implement this structure of the commodity into the MDPs.

Our pricing method currently aggregates customer decision processes $\phi_1, \ldots, \phi_n$ into parametric price elasticity model used within the transition function function of the MDPs. This is motivated by the domain that we apply our model to. In the market for EV charging services and shared vehicles, dynamic pricing is not yet widely deployed. As such, there does not exist data that could be used to model users behavior with finer granularity. However, pricing strategy such as ours, with minimal number of free parameters, could be used to collect this data. Parameters for the system could be tuned using reinforcement learning.

5 RESULTS OF DYNAMIC PRICING STRATEGY

In our experiments with the MDP based dynamic pricing strategy using a charging station datasets, we found that our method could improve charging station revenues by tens of percentage points over non-dynamic baselines and across wide ranges of demand and price elasticity parameters. Significant added benefit of dynamic pricing is that it improves utilization of resources. This is because unlike non-dynamic pricing strategies, dynamic pricing propagates information about resource availability into the utility functions of customers.

In the future, we would like to expand our work by formally describing structured commodities and developing ways of encoding these descriptions into the design of the pricing MDPs. We also plan to expand the experimental evaluation into the car-sharing domain. Within the pricing strategy, we want to include game-theoretic models of competition and of customers and to explore the possibility of learning the demand and price elasticity models with reinforcement learning.

ACKNOWLEDGMENTS

The author would like to kindly thank Michal Jakob for his supervision of this work. This research was funded by the European Union Horizon 2020 research and innovation programme under the grant agreement N°713864 and by the Grant Agency of the Czech Technical University in Prague, grant No. SGS16/235/OHK3/3T/13.

REFERENCES

[1] M.H. Albadi and E.F. El-Saadany. 2008. A summary of demand response in electricity markets. *Electric Power Systems Research* 78, 11 (2008), 1989 – 1996. https://doi.org/10.1016/j.epsr.2008.04.002

[2] Wen-Chyuan Chiang, Jason C.H. Chen, and Xiaojing Xu. 2007. An overview of research on revenue management: current issues and future research. *International Journal of Revenue Management* 1, 1 (2007), 97–128. https://ideas.repec.org/a/ids/ijrevm/v1y2007i1p97-128.html

[3] Arnoud V. den Boer. [n. d.]. Dynamic pricing and learning: historical origins, current research, and new directions. 20, 1 ([n. d.]), 1–18.

[4] S. Rasoul Etesami, Walid Saad, Narayan Mandayam, and H. Vincent Poor. 2017. Smart routing in smart grids. In *Decision and Control (CDC), 2017 IEEE 56th Annual Conference on.* IEEE, 2599–2604.

[5] Zheng Gu. 1997. Proposing a room pricing model for optimizing profitability. *International Journal of Hospitality Management* 16, 3 (1997), 273 – 277. https://doi.org/10.1016/S0278-4319(97)00015-7

[6] Michal Jakob, Zbyněk Moler, Antonín Komenda, Zhengyu Yin, Albert Xin Jiang, Matthew P. Johnson, Michal Pěchouček, and Milind Tambe. 2012. Agentpolis: towards a platform for fully agent-based modeling of multi-modal transportation. In *Proceedings of the 11th International Conference on Autonomous Agents and*

Multiagent Systems-Volume 3. International Foundation for Autonomous Agents and Multiagent Systems, 1501–1502.

[7] Shripad Kulkarni and Pushkar H. Joshi. 2017. Passenger Airline Revenue Management: Research Overview and Emerging Literature. *International Journal of Engineering and Management Research (IJEMR)* 7, 1 (2017), 387–389.

[8] Jeffrey I. McGill and Garrett J. van Ryzin. 1999. Revenue Management: Research Overview and Prospects. *Transportation Science* 33, 2 (1999), 233–256. https://doi.org/10.1287/trsc.33.2.233 arXiv:https://doi.org/10.1287/trsc.33.2.233

[9] Yanhai Xiong, Jiarui Gan, Bo An, Chunyan Miao, and Ana L. C. Bazzan. 2015. Optimal Electric Vehicle Charging Station Placement. In *Proceedings of the 24th International Conference on Artificial Intelligence (IJCAI'15)*. AAAI Press, 2662–2668. http://dl.acm.org/citation.cfm?id=2832581.2832621

[10] Yanhai Xiong, Jiarui Gan, Bo An, Chunyan Miao, and Yeng Chai Soh. 2016. Optimal pricing for efficient electric vehicle charging station management. In *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 749–757. http://dl.acm.org/citation.cfm?id=2937035