

e-Fairs: a Cyber-Physical System for Aggregation and Economy of Scale in e-Commerce

Pierluigi Gallo^{*‡} and Ignazio Gallo[†]

^{*} University of Palermo, Italy

[‡] CNIT, Italy

[†] University of Insubria, Italy

Abstract—In recent years, the e-commerce arena has deeply changed because of the advent of new business models and the growing weight of huge global actors like Amazon. Some business models create competition between users, and the product price tends to rise (e.g., online auctions); other models, including group-buying, make users cooperate, and the price tends to go down. The present study extends the group-buying model and proposes a cyber-physical system called *e-fair*, in which both sellers and buyers are grouped to negotiate on a specific product or service. E-fairs minimize the global purchase price and the shipping resources respectively with the aggregation of demand and supply as well as origins and destinations. E-fairs aggregate sellers and buyers, sources and destinations in what we call double-side aggregation. As the aggregation regards independent actors, which do not trust each other and join e-fairs in dribs and drabs, we employ a promising distributed technology as the blockchain to make the aggregation. We validated the e-fair model through a system prototype and a simulator and understood how economies of scale apply to e-fairs in different usage scenarios.

Index Terms—aggregation, e-fair, group buying, the blockchain

I. INTRODUCTION

IN recent years, the expansion of e-commerce services has led to the creation of new Internet-based business models, including auctions and group buying. Online auctions are becoming very popular both in business-to-business and in business-to-consumer markets. Auctions introduce dynamic pricing mechanisms (DPMs) where buyers also dynamically influence the sale price. The most popular methods are the English and Vickrey auction, which are adopted by players as eBay.

Group Buying (GB) business models are acquiring an essential role on the Internet as clusters of buyers obtain discounts on purchasing products and services. In some cases, there is a condition on the minimum number of requested items to finalize the purchase, as it happens with Groupon.

E-commerce platforms display deals during an auction cycle; the more buyers join the group, the lower is the unit price. The unit price drops down accordingly to a predetermined rule defined by the seller. In some cases the rule for price dynamics is public, in other cases, this information is not available to buyers. Group buying generally adopts the same price rules of wholesale purchases. However, the ordered volume comes from a single buyer in the wholesale market. Conversely, group buying aggregates many buyers in a single order.

During the early 2000s, several group-buying initiatives were born in the US including Mobshop, Mercata, CoShopper,

and LetsBuyIt; all of them have disappeared for bankruptcy or insufficient gains. This ugly performance was due to two main drawbacks. The analysis of the causes of these failures is out of the scope of this paper. However, a common factor was the incapability to capture great discounts, and the limited range of product availability¹.

The concepts of volume-based discounts and group-buying still survive and recently reappeared in different clothes. Staples.it and Groupon.com offer discounts with two different policies, with dynamic prices or with fixed prices. Staples applies prices that depend on the purchased quantity; Groupon provides one redeemable coupon only if it groups more than a pre-defined number of buyers in a time window.

To tackle the difficulties experienced by group-buying pioneers, we try to solve the problem of the availability of products by aggregating *both* buyers and sellers. We call such aggregation a double-side aggregation as it occurs at the two sides of the trading where buyers and sellers sit. Our first contribution is the definition of e-fairs, cyber-physical systems (CPSs) composed of a physical system (the selling and logistic infrastructure) and software components. Physical and digital components of e-fairs are intertwined for providing smart monitoring and control and also include humans in the loop for defining purchase selling prices and decisions.

as the tool that performs aggregation and consequent optimization; then we analyze this aggregation in a *distributed* perspective and propose the blockchain as the right tool for aggregate untrusted entities that do not know each other.

II. RELATED WORK

Studies about group buying appeared in the literature both for fixed and dynamic price. In [1], [2] the authors suggest several scenarios. In the first, they postpone production and start it only when the quantity guarantees economies of scale. e-Fairs also permit to tailor production according to the product request that comes out from the aggregation process. In the second scenario, sellers are risk-seekers who want to expand in a market by attracting price-driven buyers; they sell more products when they lower the unit prices. A similar scenario considers the presence of low-valuation demand that is greater than the high-valuation demand [3]. Few buyers accept to purchase at the high price, and many buyers exist when the price is lower. In this scenario, sellers gain more

¹Further details are available on online news of that time:
<http://www.wsj.com/articles/SB97951268061999104>,
<http://www.cnet.com/news/group-buying-site-mercata-to-shut-its-doors/>

if they adopt the group buying mechanism. The demand aggregates during a *waiting time*, whose duration influences the performance of group buying. Effects of waiting time on the financial return are studied in [4], demonstrating the presence of a trade-off between different performance factors.

Several studies explored group formation mechanism through simulation analysis and modeling. The earliest grouping websites faced difficulties aggregating a sufficient number of buyers with similar purchasing interests [5], [6]. Afterward, different strategies were used to improve grouping and in [7] it was proposed to arrange buyers in various websites. Authors of [8] introduce the concept of Combinatorial Coalition Formation (CCF), which allows buyers to announce reserve prices for combinations of products. These reserve prices and the sellers' price/quantity curves are used to determine the formation of a group for each product. The authors of [9], [10] proposed the use of a decision support system based on buyer preferences. A volume discount mechanism based on the seller's reservation price and the payment adjustment value was the approach used in [11].

Group buying works well for one type of product and even for categories of products [12]. Furthermore, buyers' web browsing history was used to recommend GB products [13]. In addition to consumers' grouping, also cooperation mechanisms for sellers have appeared in the literature. An agent-mediated electronic market was proposed in [14], [15]. To improve the grouping rate, dedicated agents recommend fair prices to sellers, based on the past buying and selling history data [16]. Aggregation presents security risks; a solution was proposed to mitigate these risks in [17], by the mean of a server for securing and monitoring transactions and of secure channels where to run the negotiation.

Group buying mechanisms impact on buyers' behavior. In [18] it was stated that buyers are influenced more by their friends than by marketers. Compelling effects were observed in [5], showing that consumers purchase more when: aggregated in large-sized groups (positive reinforcement participation); close to the time when price drops (price drop effect); the end of an auction cycle is approaching (cycle-ending effect).

Finally, three incentive mechanisms were suggested, based on time, quantity and sequence [19], [20]. The time-based incentive mechanism encourages buyers to join the group in its early days by offering an extra discount. The quantity-based incentive stimulates buyers to purchase more than planned offering extra discounts on the size of the single order. The sequence-based incentive provides discounts depending on the order of arrival of buyers; it incentivizes early arrivals.

Most of the early group buying platforms failed in the competition with large retailers from a price perspective, because of the following reasons [6]: (1) long GB auction cycles that hindered buying decision; (2) complex GB models, as perceived by buyers; (3) low transaction volumes, determining small discounts for buyers. Unlike such earlier platforms, e-Fairs jointly aggregate demand and supply for price formation, as well as providers and destinations for shipping optimization.

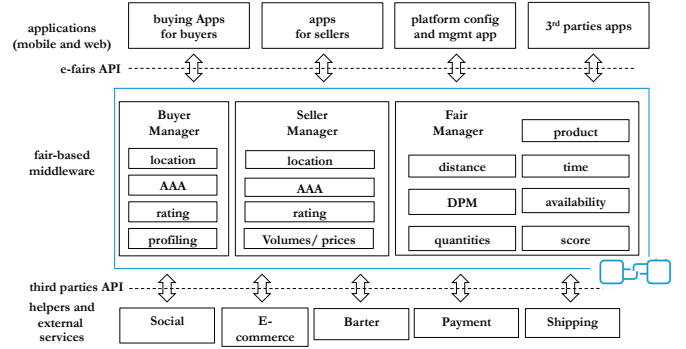


Fig. 1: The e-fair-based system architecture and relevant relationships with external existing tools and frameworks.

III. THE E-FAIR AGGREGATION MODEL

The e-fair is a new business model in which both sellers and buyers aggregate for negotiating products or service. Traditional fairs are generally held periodically. They gather goods in exhibitions and aggregate potential customers in a specific location. Sellers are also geographically aggregated in legacy fairs, and the proximity of booths permits to compare their products. e-Fairs maintain these traditional aspects and introduce new ones. Therefore e-fairs are attractive to potential buyers for the full range of products, services, and sellers that are available. E-fairs aggregate sellers looking for the best trade-off for waiting and payment time, the overall quantity of products, price/quantity curves, volumes of available goods, the location of products, shipping destinations, buyers mobility patterns.

The aggregation of sellers is both competitive and cooperative. They compete to prevail and to be selected by the e-fair as the actual supplier. Sellers implicitly cooperate as a subset of them fulfills the whole supply. However, inter-seller cooperation is neither requested nor expected, as sellers are competitors. E-Fairs integrate popular social networks to allow users were reviewing their purchasing experience in the group. Furthermore, our system offers a simple purchase workflow hiding the complexity of price optimization and seller-to-buyer assignments. Fairs work like product-oriented social communities that aggregate the demand for goods and services at the buyer side and the offer at the seller side. Buyers that join the e-fair intrinsically cooperate as their presence increases the volumes and therefore decrements the unit price; buyers provide their maximum waiting time.

The number of products ordered by one e-fair depends on the number of participants. Furthermore, if one buyer in the e-fair requests multiple ones, the total e-fair quantity increases faster. E-fairs stimulate this positive behavior by providing incentives, applying discounts and promoting social interactions. The e-fair management system systematically aggregates both buyers and sellers spontaneously aggregate in e-fairs.

IV. E-FAIR ARCHITECTURE

E-Fair system architecture appears in fig. 1, where several modules handle, configure and manage the actors

participating in e-fairs. The *buyer manager* handles buyers, their authentication into the system, their demands and profile. Sellers are handled by the *seller manager*, which also considers price/volume curves, the location of services and products. The *e-fair manager* is a critical module that handles most of the e-fair workflow: groups formation, dynamic fair handling, seller(s) selection, payment, and shipment.

The e-fair management algorithm aggregates demands and supply and decides about the status of an e-fair. This algorithm implements a smart contract: buyers join the fair by writing on the blockchain their willing to buy (in an immutable way). Every time a new buyer joins the e-fair, the smart contracts checks a specific condition (e.g., on the number of buyers), then it stops the e-fair and writes transactions related to payment and shipment. The algorithm decides how much should be paid by buyers and how much sellers receive.

The analysis of data on the blockchain permit to compute the fidelity index for buyers and sellers and several standards and distributed applications (DApps) can be developed on the top of e-fair.

Payments and shipping services can be externalized to third parties like PayPal/TNT or can be managed by functionalities of the blockchain, with a dedicated currency.

E-fairs are terminated by smart contracts when one of the exit conditions occurs (e.g., the maximum time has been reached, or a threshold discount percentage is obtained).

Data on the e-fair blockchain permit buyers and interested actors to compute *price predictions* depending on the number of aggregated buyers. This encourages buyers to be actively involved in the e-fair (e.g., buyers have an incentive to invite their friends to join the same e-fair). This social aspects of e-commerce may also have emotional value given by friendship and socialization [21].

Given price-quantity curves provided by vendors, given the e-fair ending event as discussed above, the e-fair management algorithm determines the quantities to be requested to each seller to obtain the minimum unit price and satisfy consumers' demand. The minimum price available with a specific quantity is $z_{\pi,\gamma}^*(q) = \min(z_{\pi,\gamma}(q))$.

The *quantity* $q_{\pi,\beta,\gamma}$ indicates the amount of product π requested by buyer β in the e-fair γ . Analogously $q_{\pi,\sigma,\gamma}$ indicates the amount of product π requested to seller σ in the group γ . Additionally, we consider $Q_{\pi,\gamma}$, as the *availability* of product π at the seller σ , therefore $\sum_{\gamma} q_{\pi,\sigma,\gamma} \leq Q_{\pi,\gamma}$ must hold for each seller, considering all running e-fairs. As for timing, t_{β} , is the *waiting time* before receiving the product and depends on the e-fair duration and t_{σ} is the *payment time*, that takes care if the buyer pays before, during or after receiving the product.

From the positioning point of view, our system keeps position of products and the history of buyers' positions, respectively $\mathbf{p}_{\beta} = (x_{\beta}, y_{\beta})$ and $\mathbf{p}_{\sigma} = (x_{\sigma}, y_{\sigma})$. Buyers that that communicate multiple shipping addresses obtain higher benefits than those with one shipment destination. The system correlates buyers' positions and provides suggestions for shipment aggregation. Buyers that periodically attend places in common with other buyers (e.g., schools, offices) can receive their consolidated parcel at such locations; shipment

aggregation reduces shipping costs. The position of buyers is taken by the mean of a simple positioning tool integrate into the web service and mobile application.

Incentives are given to buyers and sellers depending on their fidelity scores ϕ_{β} and ϕ_{σ} . As for buyers, these depend on their previous interaction with the system: the number of purchases, payment time (the earlier, the better), and some e-fair-related actions in social networks. Sellers have scored accordingly to the shape of their price/quantity curve (in case of registered sellers) and about the reliability of data they provide, as shipping time and availability.

As for prices, the *unit price* to be paid by the buyer β for the product π is $z_{\pi,\beta}$. Analogously the price requested by the seller σ , for the same product, is $z_{\pi,\sigma}$. Demand and supply meet in e-fairs with a unit price for product π in the e-fair γ , which we indicate as $z_{\pi,\gamma}$ and can eventually differ from both previously mentioned prices.

Additionally, the e-fair manager business model includes a small revenue upon e-fairs that reached the end of their lifecycle. The gain for the e-fair manager is the difference between the two sums in eq. 1.

$$\sum_{\beta \in \mathcal{B}_{\gamma}} z_{\pi,\beta} \geq \sum_{\sigma \in \mathcal{S}_{\gamma}} z_{\pi,\sigma} \quad (1)$$

V. SYSTEM PROTOTYPE

We designed and implemented a first system prototype to validate the feasibility of our proposed e-fair model over a real e-commerce framework.

From the available open-source platforms, we analyzed Zen Cart, OpenCart, and Magento. We finally selected OpenCart [22], as a basis to implement our idea, because of its integration with a large number of services offered by third-parties. OpenCart is a free open source e-commerce platform for online merchants, and it is available under the GNU GPL. The software is written in PHP with a MySQL database by default. OpenCart offers some features permitting to deal with unlimited products, manufacturers, and multiple shops. Although it comes with unlimited categories, some extensions have been necessary to support services rather than just products. The framework natively integrates several payment systems and shipping methods, eventually configurable for the different geographic area, which is a crucial aspect of the proposed architecture. The extensibility of the system is due to its modularity, and in a dedicated e-store, more than 9000 modules and themes are already available.

In our first prototype, we extended OpenCart functionalities adding the following capabilities: (i) handling DPM through discount factors; (ii) pricing updates depend on both the requested quantity and the product availability in stock. Prices, quantities, and other relevant parameters have been implemented as multiplicative factors; (iv) user's position is taken and stored in the database, for user profiling and shipping optimization, by the mean of an Ajax call; (v) sellers provide their multi-dimensional pricing strategies.

VI. USE CASES

We describe the whole workflow for e-fair management using an example. Let's consider having a buyer that wants

to buy a smartphone, which can be found online at a price of 100 currency units (CUs). After logging into the system using private credentials, buyers check if existing e-fairs are already running about the desired object (category and model). If there is no running e-fair for the demanded product, the buyer launches a new one. Opening the e-fair, he describes the product category and provides parameters about the desired discount rate, time constraints, payment constraints. In case the desired product is not available among those supplied by registered sellers, the platform interrogates external e-commerce portals (e-bay, Groupon, Amazon), to return an answer to the questing buyer. The lack of an answer would be frustrating for potential users with a lack of products, which can be probable during the starting period when the number of registered sellers and products is not high. Of course, having no price/quantity curves available, the only benefits would be those of shipping aggregation.

As for sellers, they access a dedicated section where they define the price/quantity curve by providing its parameters or through a table. When the e-fair goes to its end, all buyers involved receive a notification with the final price and pay their remaining quote. The system optimizes shipping services after determining quantities to be requested to each seller and computed the *best shipping routing* between sellers and buyers.

Fairs also deal with services, and in this case, we refer to customers and providers. *Entertainment services* (tickets for museums, cruise, flights, ...), *health services* (medical treatments), and *learning services* (private lessons) can be dealt with e-fairs. Services permit to aggregate consumers on time. Both *sequential* and *concurrent* aggregations are possible as customers can use the service concurrently (e.g., in a cinema) or sequentially (e.g., scheduled wellness treatments in a beauty farm).

VII. RESULTS

In this section, we show results obtained by our aggregation mechanism. Being aggregation at the buyer side extensively covered in the literature, we aggregate at the buyer-side and obtain the total number of demanded items; then we focus on aggregation at the seller side.

To validate our aggregation methodology we used both the system prototype described in Sect. V and an ad-hoc simulator is written in Matlab, to test aggregation over a large number of sellers and buyers.

A. Dynamic pricing model for the single seller

Fig. 2 reports the dynamic pricing models for the single seller. Among the test campaign we run, we show results using 20 sellers providing as many curves of unit price/quantity, for the same good.

Our aggregation middleware supports whatever shape of dynamic pricing model for sellers, which can provide the price as (continuous) functions of the demanded quantity or as (discrete) two-columns table: quantity and price. For the sake of simplicity, without lack of generality, we modeled price/quantity curves as broken lines: they are slopes till a certain number of demanded products, then they turn into

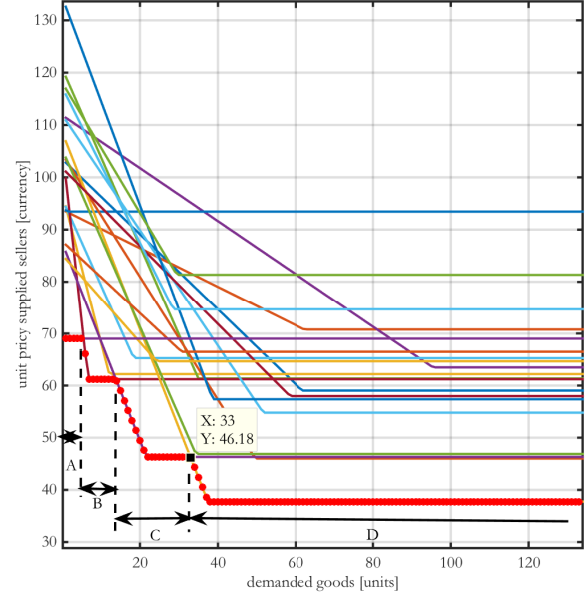


Fig. 2: Price/quantity diagrams for a single product. Each line represents the curve for a different seller. The curve defines how the unit price changes while varying the demand.

the plateau. Despite its simplicity, this model is realistic because the angular coefficients represent constant discount rates. From a value on, slopes become the plateau, modeling the saturation effect because selling unit price cannot be lower than production-related costs.

The lowest broken line in bold red indicates the lower envelope of DPM curves and is the unit price obtained by the e-fair (all sellers), under the assumption that each seller has infinite supply availability. Under this condition, given the number of demanded products, all of them are available (and bought too) a single seller. However, depending on the quantity, the most convenient seller can vary. As, if the requested quantity is in the range 1 to 5 units, the best seller to select is A, from 5 to 13 is B, from 13 to 33 is C and from 33 on is D, as delimited by vertical dashed segments and indicated by black arrows in fig. 2.

These DPM models are independent of each other and are entirely defined by three parameters: (i) the single-product unit price, in case of one product (the intersection with y-axis), (ii) the discount rate (the angular coefficient of the slope), (iii) the saturation price (the height of the plateau). Values used in tests are obtained using distributions reported in table I. For the sake of generalization, we use generic currency units (CU) instead of \$, £, €.

B. Dynamic pricing model for the whole e-fair

Unlike the dynamic pricing model for the single seller, the DPM for the e-fair can be non-monotone. This happens because after the most convenient seller terminates products in stock, the system has to consider the second choice, then

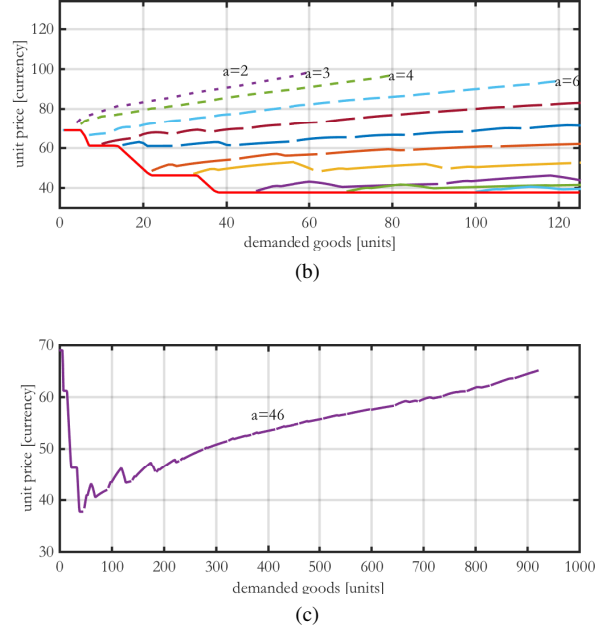
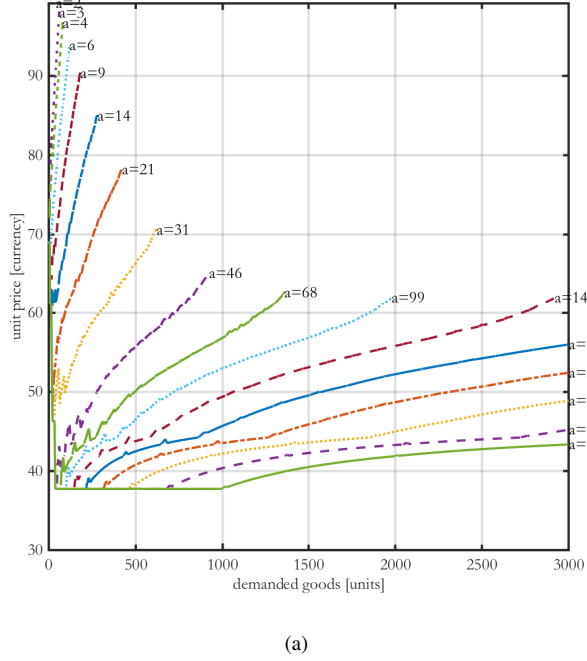


Fig. 3: Dynamic pricing model for the e-fair, due to sellers aggregation. Each curve shows the trend of the unit price by varying the demanded amount. Curves are (logarithmically) parametrized depending on the number of products available at each seller (a). The same diagram shown on the left, zoomed to better show its left-most side (b). The price curve when all sellers have 46 products (c).

TABLE I: Parameter values used in simulation

DPM parameter	Distribution	Dist. params
<i>single – product unit price</i>	Normal	$\mu = 100 \text{ CU}$ $\sigma = 20 \text{ CU}$
<i> discount rate </i>	Lognormal	$\mu = -2 \text{ CU}/u$ $\sigma = 2 \text{ CU}$
<i>saturation price</i>	Normal	$\mu = 60 \text{ CU}$ $\sigma = 12 \text{ CU}$

Realistic distribution kind and parameters for DPM for a single seller. These may depend on the category of product and on the elasticity of demand and supply.

the second, etc. The unit price, in such a case is not anymore computed directly on price/quantity curves but using a function of a weighted sum:

$$z_{\pi, \gamma}(q_{\gamma}) = l \left(\frac{\sum_{\sigma \in \mathcal{S}_{\gamma}} q_{\pi, \sigma, \gamma} \cdot z_{\pi, \sigma}}{\sum_{\sigma \in \mathcal{S}_{\gamma}} q_{\pi, \sigma, \gamma}} \right) \quad (2)$$

In our case, we used the function $l(x) = x$, therefore directly the weighted sum.

In fig. 3(a) we present pricing curves obtaining aggregating sellers with a *finite supply availability*, homogeneous on all sellers. The more products are available at each seller, and the more the curve moves towards, the lower right corner of the figure. Different phenomena can be explained by the mean of (b) and (c), both obtained by (a) using different zooms. In

fig. 3(b), it is possible to recognize the same red steps shown in fig. 3. These steps are the asymptotic diagram to which e-fair-based price/quantity curves tend when the number of products available at each seller tends to infinity. On the other hand, in (c) it is possible to see the price curve when all sellers have 46 products. This curve has a plateau at its minimum, which represents the optimal aggregation range. When the demand is in the range between 38 and 45 products, the e-fair has its optimal performance, considering the maximum number of products available at the best seller.

VIII. CONCLUSION AND FUTURE WORK

This paper presents a novel aggregation model for both buyers and sellers, paving the road to new possibilities in e-commerce scenarios.

Some features of our model come from group buying, others from auctions systems but the resulting system lays at the intersection of these two concepts, and introduces the double-side aggregation at buyers and sellers. In systems like e-bay, prices increase due to competing buyers in the auction, while in our system prices become lower due to users' cooperative aggregation. However, in a more generic model, which also includes shipping and auxiliary costs, prices/quantity curves are not monotonically descent with the number of goods. This non-monotonic trend requires the solution of an optimization problem, which is computed by the e-fair manager module. The output of this algorithm is expected to provide the minimum unit price and the optimal quantity to be provided by each seller.

Effects of elastic demand/supply models over the system should be investigated, as well as the case of different availabilities at different sellers and how different factors interact each other (e.g., the best price seller for a specific quantity may have more expensive delivery fares).

This preliminary work provides encouraging results and stimulates further investigations on buyers and sellers aggregation according to the e-fair-based model. As future work, we consider adding incentivizing mechanisms for buyers and sellers and studying the effects of smart contracts on automatic e-fair handling.

ACKNOWLEDGMENT

7Pixel S.r.l has supported this work. The authors thank Francesco Randazzo for his preliminary analysis of related work.

REFERENCES

- [1] K. S. Anand and R. Aron, "Group buying on the web: A comparison of price-discovery mechanisms," *Management Science*, vol. 49, no. 11, pp. 1546–1562, 2003. [Online]. Available: <http://dx.doi.org/10.1287/mnsc.49.11.1546.20582>
- [2] J. Chen, X. Chen, and X. Song, "Comparison of the group-buying auction and the fixed pricing mechanism," *Decision Support Systems*, vol. 43, no. 2, pp. 445–459, 2007.
- [3] J. Chen, R. J. Kauffman, Y. Liu, and X. Song, "Segmenting uncertain demand in group-buying auctions," *Electronic Commerce Research and Applications*, vol. 9, no. 2, pp. 126–147, 2010.
- [4] H. Sharif-Paghaleh, "Analysis of the waiting time effects on the financial return and the order fulfillment in web-based group buying mechanisms," in *Proceedings of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology-Volume 01*. IEEE Computer Society, 2009, pp. 663–666.
- [5] R. J. Kauffman and B. Wang, "New buyers' arrival under dynamic pricing market microstructure: The case of group-buying discounts on the internet," *Journal of Management Information Systems*, vol. 18, no. 2, pp. 157–188, 2001.
- [6] —, "Bid together, buy together: On the efficacy of group-buying business models in internet-based selling," pp. 99–137, 2002.
- [15] T. Ito, H. Ochi, and T. Shintani, "A group-buy protocol based on coalition formation for agent-mediated e-commerce," *IJCIS*, vol. 3, no. 1, pp. 11–20, 2002.
- [7] M. Hyodo, T. Matsuo, and T. Ito, "An optimal coalition formation among buyer agents based on a genetic algorithm," in *Developments in Applied Artificial Intelligence*. Springer, 2003, pp. 759–767.
- [8] C. Li, K. Sycara, and A. Scheller-Wolf, "Combinatorial coalition formation for multi-item group-buying with heterogeneous customers," *Decision Support Systems*, vol. 49, no. 1, pp. 1–13, 2010.
- [9] T. Matsuo and T. Ito, "A decision support system for group buying based on buyers' preferences in electronic commerce," in *the proceedings of the Eleventh World Wide Web International Conference (WWW-2002)*, 2002, pp. 84–89.
- [10] —, "A group formation support system based on substitute goods in group buying," *Systems and Computers in Japan*, vol. 35, no. 10, pp. 23–31, 2004.
- [11] T. Matsuo, "A reassuring mechanism design for traders in electronic group buying," *Applied Artificial Intelligence*, vol. 23, no. 1, pp. 1–15, 2009.
- [12] J. Yamamoto and K. Sycara, "A stable and efficient buyer coalition formation scheme for e-marketplaces," in *Proceedings of the fifth international conference on Autonomous agents*. ACM, 2001, pp. 576–583.
- [13] T. Chen, "Towards convenient customer-driven group-buying: an intelligent centralised p2p system," *International Journal of Technology Intelligence and Planning*, vol. 8, no. 1, pp. 16–31, 2012.
- [14] T. Ito, H. Hattori, and T. Shintani, "A cooperative exchanging mechanism among seller agents for group-based sales," *Electronic Commerce Research and Applications*, vol. 1, no. 2, pp. 138–149, 2002.
- [16] Y. K. Lee, S. W. Kim, M. J. Ko, and S. E. Park, "Pricing agents for a group buying system," in *EurAsia-ICT 2002: Information and Communication Technology*. Springer, 2002, pp. 693–700.
- [17] J.-S. Lee and K.-S. Lin, "An innovative electronic group-buying system for mobile commerce," *Electronic Commerce Research and Applications*, vol. 12, no. 1, pp. 1–13, 2013.
- [18] M. Lai and C. Su, "An empirical test of the effectiveness of communication source: A case of group buy," in *Proceedings of the 13th Asia Pacific Management Conference, Melbourne, Australia*, 2007, pp. 1263–1269.
- [19] H. Lai and Y. Zhuang, "Comparing the performance of group-buying models with different incentive mechanisms," in *Proceedings of the Third Workshop on e-Business*, 2004, pp. 1–12.
- [20] H. Lai and Y.-T. Zhuang, "Comparing the performance of group-buying models-time based vs. quantity based extra incentives," in *Proceedings of the Fourth Workshop on Knowledge Economy and Electronic Commerce*, 2006, pp. 81–90.
- [21] L. Bucci, "From e-commerce to social commerce: exploring global trends," 2014.
- [22] "Opencart - open source shopping cart solution."