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ON-DEMAND LOGISTICS SERVICE FOR PACKAGES: PACKAGE BIDDING MECHANISM VS. PLATFORM PRICING

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ABSTRACT

This paper is an exploratory analysis of an on-demand service platform for packages, where the packages bid for transportation service through various auction mechanisms, trucks offer transportation services, and distribution centers match demand and supply. All agents are independent and individually incentivized to participate. Using a utility-based model, we characterize the participation incentives for all the agents, implement the state-of-the-art pricing mechanisms from industry and academia, and design and implement a first-price auction-based mechanism. Using simulation and through performance indicators like throughput, profit of the distribution center, consumer surplus, among others, we find that the package bidding mechanism significantly outperforms the status quo. Furthermore, we extend our analysis to include uniform price and Vickrey-Clarke-Groves auctions. We find that the packages prefer the Vickrey-Clarke-Groves auction, whereas the trucks and distribution centers prefer the first-price auction; although all of them prefer the bidding mechanism to the status-quo pricing mechanism.

1 INTRODUCTION

Disruptive Economics refers to the new business models that – through technological innovation – disrupt and cannibalize existing businesses (Naughton 2014), and these disruptions are getting more and more prevalent owing to the ubiquity of the internet. In the transportation and logistics industry, and specifically, the urban transportation industry, ride-hailing companies have revolutionized and changed the way customers travel between an origin and destination (OD) pair. For better or for worse, different aspects of urban transportation like owning personal vehicles, taxi service prices, and congestion have been affected by the presence of ride-hailing companies (Acheampong et al. 2020, Kamargianni and Matyas 2015). However, despite these advances, some fundamental market forces have remained constant; for example, the consumers are still the price takers, i.e., ride-hailing companies quote a take-it-or-leave-it price to the consumers, who then decide whether or not to participate (Uber 2021). Consequently, the demand for such services is primarily driven by the price quoted by the platform. Also, the objective of these companies remains profit maximization with scant attention given to consumer surplus maximization.

In the logistics industry, trucks hauled 72.5 % of all freight transported in 2019 and generated revenue of \$791.7 billion in 2019 (American Trucking Association 2020). One of the major challenges that this industry faces is the under-utilization of truck capacity (MAI 2021), resulting in moderate to large transportation companies losing money due to the associated sunk costs. Some firms tried to address this issue by designing their operations similar to ride-hailing companies and offering transport between an OD pair for packages. We use the terms customer and package interchangeably, e.g., Uber Freight, Convoy. Their operating principle resembles the existing ride-hailing companies – the person sending a package requests transportation service for a given package through a platform, he or she is quoted a price by the platform and then the sender decides whether to accept the price or not. Finally, the sender is matched with a service provider who agrees to accept a fraction of the quoted price as wages (UberFreight 2021). However, these companies have not been able to cannibalize the traditional companies in the logistics industry like FedEx or UPS. This can be, in part, ascribed to the fact that this business model is not particularly suited for packages owing to different sensitivity to waiting, different payment structures, and different capacity constraints (Forbes 2018; Doft 2021); however, these factors do not completely explain the lack of success. Factors like pricing strategies and prioritizing profits also affect demand and, consequently, market penetration. It is worth noting that the sender is still a price taker and demand is driven primarily by the price quoted by the platform, as in the case with ride-hailing services.

In this exploratory paper, we focus on the logistics industry and propose an alternative system for implementing package transportation across different geographic locations. Specifically, we focus on settings where the customers bid for transportation services within an auction environment rather than being quoted a price by the service providers. We are motivated by the lack of disruption in this traditional industry and are aware of avenues to improve efficiency as well as consumer welfare by bringing the cost to the customer down and driving demand through an auction-based bidding mechanism. Our proposal can be seen either as a policy decision by the government, for example through the state-owned carrier USPS to make this market more efficient, or as an operational model by a technology company looking to disrupt traditional businesses. Consequently, this research aims to characterize a new mechanism, inspired by the auctions, to match demand and supply in the logistics industry, and compare it with current mechanisms adopted by industry experts and academicians.

To address the research objective and gain insight into the operations model, we build a stylized model with consumers, trucks, and distribution centers (DC). Using a utility-based model, given problem parameters, and using an auction-based bidding process, we elicit the optimal decision for all the agents involved. Finally, using simulation we solve the problem computationally and elicit insights into different performance indicators. Furthermore, we analyze several extensions by relaxing some of the assumptions to highlight the performance of our proposed mechanism as well as ensuring robustness. The findings address the failure of the companies in disrupting traditional logistics companies as well as contribute to the development of new mechanisms to drive demand and efficiently match supply. From a practitioner's point of view, our findings show the efficacy of the proposed auction-based bidding by the packages across different performance indicators against the state-of-the-art industry practices. Furthermore, our study also paves ways for future research towards mechanisms that are more efficient and benefit all the involved agents through both theoretical and computational analysis.

The rest of the paper is structured as follows. In Section 2, we present an overview of the relevant literature. In Section 3, we present the context and explain the modeling methodology. We describe the experimental setup and results in Section 4. In Section 5, we discuss some extensions to further showcase the attractiveness and robustness of our model, and finally, in Section 6, we present concluding remarks, insights as well as future research directions. We present an illustrative numerical example in the Appendix.

2 LITERATURE REVIEW

This paper belongs to the growing stream of literature in two-sided markets where platforms facilitate the exchange of services between demand and supply, and we refer the readers to Rochet and Tirole (2003), Rysman (2009), and Parker and Van Alstyne (2005) for a variety of contexts and market structures. We focus on on-demand service platforms for logistics, in which customers demand service immediately and are sensitive to waiting time and prices while the drivers are sensitive to wages.

With respect to the analysis of on-demand service platforms, most of the research is focused on finding the equilibrium structure of parameters like optimal pricing structure, efficient matching, and efficient staffing (Banerjee et al. 2015; Bai et al. 2019; Taylor 2018). Since our focus is to evaluate a pricing mechanism, we use results from papers that focus on pricing, as a benchmark against which we compare our proposed mechanism. Banerjee et al. (2015) uses a queuing-theoretic economic model to compare dynamic pricing and static pricing under stochastic demand. Taylor (2018) uses a similar queuing formulation and examines how various sources of uncertainty, like congestion-driven delay and heterogeneity in valuations, affect the optimal price and wage. Finally, Bai et al. (2019), who use a similar model as the two papers listed above, focuses on influencing the supply and demand through price and wages with impatient customers. With respect to context and modeling approach, these papers are closest to our research. All of these papers share a common theme, they use $M/M/k$ queue to model a ride-hailing platform and, with varying degrees of differences, elicit the optimal pricing structure. We use the results in these papers to model the base scenario in our study with some contextual changes.

The application of ride-hailing platforms in supply chain and logistics has received scant attention from both academia as well as practitioners. Qi et al. (2018) focus on the last-mile delivery and how the traditional last-mile delivery compares with a new paradigm of using ride-hailing platforms for last-mile deliveries. They find that while ride-hailing services might not be scalable as trucks, some compelling benefits warrant a serious study. Our work seamlessly complements their paper, because we model the operational and pricing aspects of the logistics of the packages before the last-mile delivery, i.e., between DCs and other smaller DCs in the network hierarchy. Also, it is important to point out that our work is distinct from the crowd shipping literature; crowd shipping refers to harnessing the already traveling users to transport goods (Simoni et al. 2019), but we are solely focusing on traditional modes of transportation, albeit, through a new mechanism.

We also draw upon the concepts of auction theory and mechanism design to design and implement our proposed mechanism, which involves the packages bidding under a given auction mechanism. We abstract away from a rigorous economic analysis of auctions; rather we use established methodologies and tailor them contextually. We direct the interested readers to Krishna (2009) for a fundamental and excellent treatment on the subject. Finally, within this stream, we refer to the seminal work of Vickrey (1961), Clarke (1971), and Groves (1973) which provide a framework for designing auction mechanisms. For the practical applications of auction theory and mechanism design to logistics and supply chain problems, we refer the readers to Kuyzu et al. (2015), Qiao et al. (2020), Xu and Huang (2014), Lafkihi et al. (2019), and Huang and Xu (2013). Finally, simulation has long been used to analyze dynamic systems which cannot be analyzed analytically. We refer the reader to Barenji et al. (2019), Fatnassi et al. (2015), Van Duin et al. (2007), and Janssen and Verbraeck (2008) for a representative example of how simulation is used to model logistic systems and elicit operational insights.

3 MODEL AND PRICING MECHANISMS

We consider a logistics setup that deals with the transportation of packages between DCs and focus our attention on all the involved agents, DCs, packages that need to be transported, and the trucks that transport the packages. We assume that all the agents are independent and participate only when they are sufficiently incentivized. Before describing the central aspects of the model, it is useful to provide a high-level description of the timeline of events here. When a package has to be sent between an OD pair, the sender goes to the nearest DC, observes the waiting time for service, number of packages vying for the same service, and pays a certain amount, p, while requesting transportation. We use two mechanisms to derive p: (i) Two-Sided Platform Pricing, which can be considered as status quo, and (ii) Package Bid Pricing, which is our proposed mechanism. Both are described later in this section. The DC offers a fraction, δ, of this price, p, to trucks as wages for offering transportation as a service. Trucks who find this wage, $w = \delta p$, sufficient, accept the request. The DC's revenue stream, per package, stems from the fraction of the price paid by the packages in lieu of facilitating the matching of packages and trucks, $\pi = p(1-\delta)$. We now present the modeling details concerning the agents and the pricing schemes.

3.1 Customers

Following Bai et al. (2019), Taylor (2018), and Banerjee et al. (2015), we use a queuing theoretic framework to model the customers. To be specific, we use an $M/M/k$ queue to model customer arrival and define a utility-based formulation to model customer decisions. Customers arrive at the DC randomly at a rate λ following a Poisson process. Each package has three characteristics, valuation (v), weight (M), and destination distance (D); all the packages require unit capacity. We define valuation as the maximum the customer is willing to pay to transport the package, and it is drawn from a continuous distribution with a known probability distribution ($f_v(.)$), cumulative distribution ($F_v(.)$) function with a support of $[0,1]$. The weight and destination distance are independent random variables drawn from known distributions with known expectations and variances, $\mathbb{E}[M] = m$, $\mathbb{E}[D] = d$. Since the standard unit for freight pricing is 'weight-distance', for example 'ton-mile' (USEIA 2021), we define the service requested by the package as a product of its weight and distance, MD. We define the utility function of a customer as $u_p = v - pMD - cW_q$, where p is the price paid by the package, c is the sensitivity of the packages to the waiting time and W_q is the expected waiting time. The package requests service only if it gains non-negative utility from the transaction, hence, the actual rate of arrival is given by

$$\begin{aligned}\lambda_a &= \lambda \mathbb{P}(u_p \geq 0) \\ &= \lambda \mathbb{P}(v \geq pMD + cW_q).\end{aligned}$$

We assume that the packages do not know how many units the trucks can accommodate; in other words, the packages always bid as if the trucks can only accommodate a single package. We make this assumption here for the sake of tractability, simplicity, and eliciting insights from a simple modeling framework. We later relax this assumption in Section 5 and analyze the ensuing scenario.

3.2 Trucks

From the supply side, there are K trucks registered in the system and they are heterogeneous with respect to their outside options, o. Here, outside options refer to other employment avenues like regular logistics hauling services. We assume that o is drawn from a known probability and cumulative distribution, $g_o(.)$ and $G_o(.)$, respectively, with support between $[0,1]$. Only those trucks who make at least as much as their outside option join this system and we define that fraction as β. The expected earning rate, e, for a truck in this system is given by, $e = w\mu MD\rho$, where μ is the service rate of the trucks which we assume to be exponentially distributed and ρ is the utilization of the system, which is given by $\frac{\lambda}{\mu k}$ and k is the number of active trucks in the system at that instance. The trucks select the load bid (i.e., the set of packages they choose to carry) by selecting the packages in decreasing order of their bids based on their capacity. We define the capacity of a truck by the number of packages it can hold. Once the truck accepts a load bid, it goes away from the system for the service duration and again becomes active or online following successful completion of the delivery.

3.3 DC

The DC facilitates the matching between the trucks and the packages and its revenue stream is a fraction of the amount paid by the packages who participate. The DC offers the price that a participating customer is willing to pay to the nearest active truck and continues to offer the quote to trucks in increasing order of distance until it is accepted. The profit function of the DC is given by, $\Pi_{DC} = \lambda(p - w)MD$.

3.4 Two-Sided Platform Pricing

We follow Bai et al. (2019) to establish this model, with some contextual changes, as the status-quo pricing scheme. In this system, the DC plays the role of a two-sided platform, with packages demanding service and trucks offering service forming the two sides. Once packages arrive, the DC shows an expected waiting time to the package which is based on the $M/M/k$ framework, and quotes the price p. Once the packages accept this price, conditional on gaining net positive utility, the DC offers a fraction of this price to the trucks as wages, $w = \delta p$. Similarly, trucks, conditional on earning at least as much as their outside option, accept this request. It is worth noting that the DC can influence the participation of both packages and trucks by setting p and w, accordingly. The price, p, charged by the DC, as a function of λ is given by,

$$p = \frac{1}{md} F_v^{-1}\left(1 - \frac{\lambda_a}{\lambda}\right) - \frac{c}{md} W_q$$

Since trucks who make at least as much as their outside option will join this system and we define that fraction as $\beta = G_o(\frac{wd\lambda_a}{k})$. We have $k = \beta K$. We can now write the wage of a truck in this system, $w = G_o^{-1}(\frac{k}{K})\frac{k}{md\lambda_a}$. Finally, the profit function of the DC is given by,

$$\Pi_{DC} = \lambda_a \left[\frac{1}{md} F_v^{-1}\left(1 - \frac{\lambda_a}{\lambda}\right) - \frac{c}{md} W_q - G_o^{-1}\left(\frac{k}{K}\right)\frac{k}{md\lambda_a}\right] md$$

We have an implicit constraint here that ensures the stability of the queue, $\rho < 1$. Also, we have the fixed pay-out ratio of price and wages, i.e., $w = \delta p$, which adds an equality constraint to our model. Putting together the objective function and the constraints gives us the required constrained optimization problem, whose solution indicates the optimal price. Thus, the optimal price charged by the platform is given by the solution of the following constrained optimization problem:

$$\begin{aligned} \max_{k,\lambda} \ & \Pi_{DC} \\ s.t. \ & \rho < 1 \\ & w = \delta p \end{aligned}$$

3.5 Package Bid Mechanism

From the supply side, there are K trucks registered in the system and they are heterogeneous with respect to their outside options, o. Here, outside options refer to other employment avenues like regular logistics hauling services. In our proposed mechanism, instead of the DC setting the price, we allow the packages to bid based on their valuations through an auction environment. Consistent with the auction literature and our assumptions, evidenced from reality, the valuations are independent and private knowledge. This changes the dynamics of the system drastically, because now the DC cannot influence the arrivals of the packages and trucks by adjusting p. On the contrary, the packages determine their optimal bids based on the auction format. The rate of arrival of the packages is the same as above, λ, and once the package arrives, it observes the number of packages currently waiting for service and the expected waiting time. Given these values, the package determines its optimal bidding strategy, and consequently, the optimal bid. The package only requests service if it gains a non-negative utility from the service. We also allow the packages to update their bid every time there is an arrival from the system to be fair to all packages and not implicitly favor packages that come in early or late. In contrast to the DC setting prices and thus influencing demand, in this scenario, the demand or package participation is driven by their valuations and bidding strategies. We analyze a first-price auction environment in this section; in Section 5, we analyze a uniform price auction as well as a Vickrey-Clarke-Groves (VCG) auction. Within a first price auction environment, an incoming package, with a bid of b_n, wants to maximize its utility, which is defined as, $u_p = v - cW_q - b_n$. However, it will only gain a positive utility if it is selected by the truck, i.e., the package's bid is highest of all the bids. Thus, the actual utility function that a package seeks to maximize is given by

$$(v - cW_q - b_n)\mathbb{P}(b_1 < b_n, b_2 < b_n, \ldots, b_{n-1} < b_n).$$

Following our assumption of independence, the package thus solves the following optimization problem:

$$\max_{b_n}(v - cW_q - b_n)\mathbb{P}(b_1 < b_n)\mathbb{P}(b_2 < b_n)\dots\mathbb{P}(b_{n-1} < b_n) \tag{1}$$

Solving (1) by taking the first order derivative with respect to b_n and setting it to 0, we get the optimal bidding strategy adopted by the packages. The optimal bid, b_n, of an incoming package, when there are $n-1$ packages in the system, is given by

$$b_n = \frac{n-1}{n}(v - cW_q).$$

4 EXPERIMENTAL SETUP AND RESULTS

In this section, we describe our simulation set-up as well as the performance indicators and provide a representative analysis of the simulation results. Owing to the dynamic nature of the setup and lack of analytical tractability, we implement a discrete event simulation to model both mechanisms using the 2019b version of MATLAB. This enables us to implement the dynamics of different mechanisms, analyze the output, and derive insights. We first implement the platform pricing mechanism, then we implement the package bidding mechanism, and finally compare the output through some performance indicators, described in the subsequent section.

4.1 Initialization

We generate values for the input parameters in order to initialize our system with two types of input parameters: stochastic and deterministic. Stochastic parameters are generated randomly using predefined distributions, and deterministic parameters remain constant throughout. We use the following numerical distributions for the input parameters to present an illustrative example and analysis in the subsequent sections, $\lambda \sim PP(10)$, $\mu \sim exp(5)$, $v \sim \mathscr{U}[25,50]$, $M \sim \mathscr{U}[25,50]$, $D \sim exp(12)$, $o \sim \mathscr{U}[80,120]$, $c = 5$, $K = 100$, and, $\delta = 0.8$. Then, we implement the two mechanisms using results from Section 3. Since we use the same set of input parameters to simulate the two different mechanisms and extensions, the results serve to illustrate the ordinal performance of the mechanisms rather than absolute performance, which would require rigorous normalization and parametrization. Thus, although the choice of parameters does impact the absolute performance, from a pure comparison point of view, any set of feasible input parameters, which remain the same for all mechanisms, are sufficient to illustrate which of the two mechanisms is beneficial. The use of different ranges and underlying distributions for the stochastic problem parameters does not affect our results.

4.2 Performance Indicators

To evaluate the performance of the package bidding mechanism and to ensure that all the agents have the incentive to participate in such a mechanism, we focus on the following performance indicators.

Within our framework, the DC plays an important role under both mechanisms. The DC influences the demand by setting the price and wages under the two-sided platform pricing mechanism, whereas, in the package bidding mechanism, the DC matches demand and supply. Since the revenue stream of the DC depends on a fraction of what the participating customers pay, the DC has an implicit incentive to join a mechanism that maximizes its throughput. Hence, we compare the throughput at the DC under different mechanisms to evaluate which mechanism leads to higher throughput.

Higher throughput does not automatically translate to higher profit for the DC, because in the pricing mechanism the DC might end up with high earning from a low throughput due to the high price charged per customer. In contrast, if the bids are sufficiently low in the package bidding mechanism, then even with high throughput, the total earning might be less. Hence, we want to evaluate, given the same set of valuations and service requests, which mechanism leads to higher profits for the DC, thus incentivizing participation.

The price paid by the customers determines the demand in either of the mechanisms. However, it is not trivial which of the mechanism is beneficial to the packages, because of variability in a multitude of parameters like service units requested and valuation or willingness to pay. While a package with a high valuation might find the platform pricing mechanism acceptable because of a possibly low quoted price, a package with a low valuation will certainly prefer the package bidding mechanism owing to the fact that a smaller bid has a possibility of getting accepted. We compare the actual price paid by the customers under the two mechanisms with respect to its valuation.

The actual time spent by the package waiting to get picked by a truck is an important indicator of the efficiency of service. Also, the actual amount that the trucks earn from a mechanism is indicative of the attractiveness of the system which influences the number of active trucks offering their services. Thus, we elicit these metrics from our simulation to gain insight into the attractiveness of a mechanism.

4.3 Sequence of Events

Following initialization, the DC offers the bids or prices of participating packages to the nearest truck. Depending on the truck's outside option and capacity, the truck selects a load bid and leaves the system for the duration of the service period, i.e., time taken to deliver the package, and re-enters after delivery is complete. However, if the nearest truck rejects the load bid, the DC offers the set of bids or prices to the next-nearest truck and continues the process. To maintain computational tractability, we limit our time duration to 1,000 time units. Following the completion of the predefined time horizon, we extract the performance indicators described in the previous section. Finally, to gain an understanding of the long-run behavior of the system, we replicate a Monte Carlo simulation 10,000 times and analyze the expected or long-run average values of the performance indicators. The sequence of events is illustrated in Figure 1.

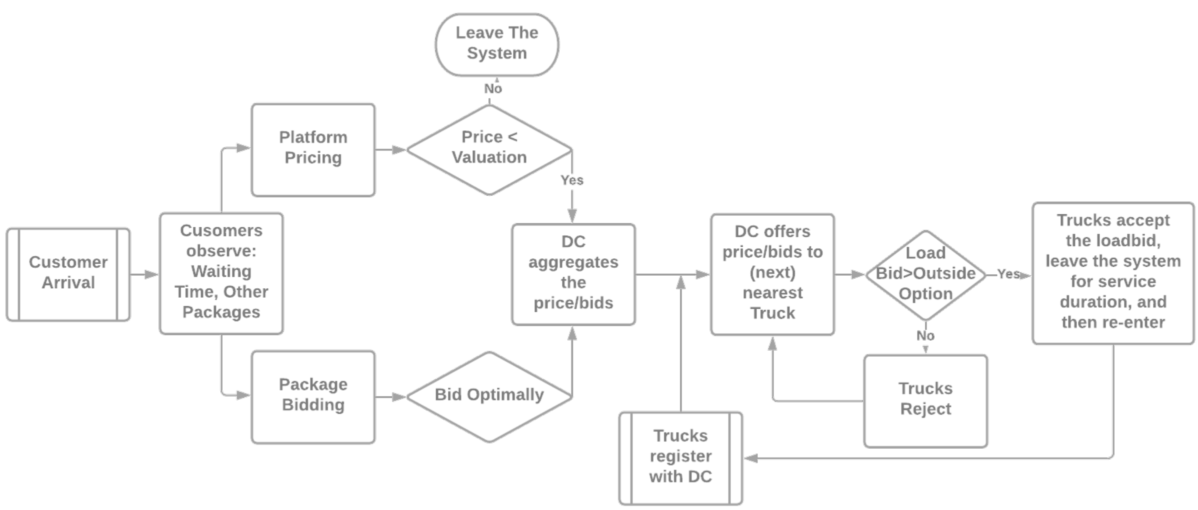


Figure 1: Sequence of events.

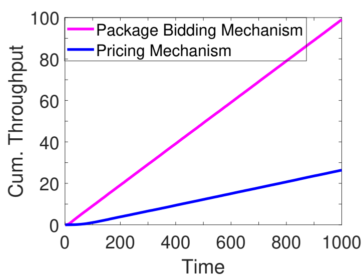
4.4 Numerical Analysis

Our results indicate that the package bidding mechanism outperforms the platform pricing mechanism by a significant margin. From the point of view of throughput at a DC, since demand is now driven by the bids, more packages find it worthwhile to participate. According to more packages using the system, the profit at the DC also increases as compared to the platform pricing. Finally, since packages indulge in shade bidding, i.e., bidding less than their valuation, the amount they eventually pay is also less than their

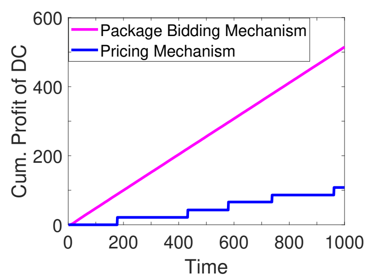
Table 1: Package waiting times and trucks' earnings.

Mechanism	Average Number of Active Trucks	Average Earnings	Average Waiting Time of Packages
Platform Pricing	5.34	87.16	233 ($\pm$ 119.46)
Package Bidding	22.143	93.0157	18.619 ($\pm$ 18.977)

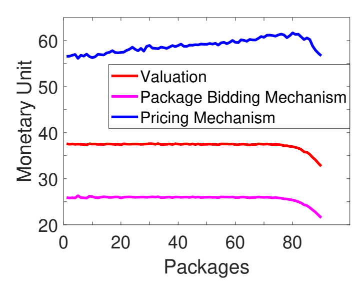
valuation and significantly less than the amount charged under the platform pricing mechanism. Table 1 and Figure 2 detail the numerical output of our simulation model. From Table 1, we see that the number of active trucks almost increases by 300 % under the package bidding mechanism with an increase of almost 7 % in earnings. From the point of view of the packages, under the package bid mechanism, their waiting time decreases by almost 90 %. Furthermore, the packages pay around 32 % less than their valuation and 52 % less than the amount charged under the platform pricing mechanism. Finally, from the DC's point of view, the throughput and the profit increase by 400 % and 500 %, respectively under the package bid mechanism. One of the reasons the package bid mechanism comprehensively outperforms the platform pricing mechanism is that the demand is driven by the package bids. The platform, DC, in this case, plays a passive role of matching demand and supply rather than affecting demand and supply through setting price and wages. Thus, even though the packages end up paying less than under platform pricing, the volume of throughput ensures a higher profit.



(a)



(b)



(c)

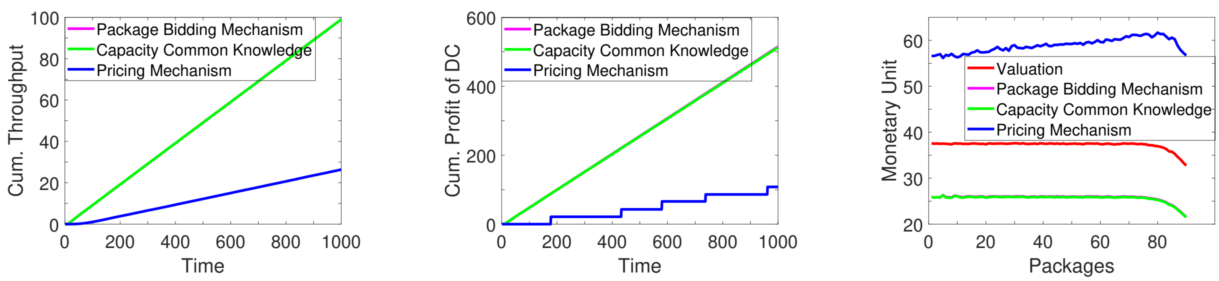
Figure 2: Package bid mechanism vs. platform pricing: (a) cumulative throughput at DC, (b) cumulative profit of DC, and (c) amount paid by the customer.

5 EXTENSIONS

In this section, we relax some assumptions from Section 3 and analyze other widely-used auction mechanisms. In the first extension, we relax the assumption that the packages do not know the capacity of the trucks, and hence, bid for unit capacity. We relax this assumption and assume that the truck's capacity is common knowledge. Consequently, this takes the form of a uniform price auction. Subsequently, we analyze another form of auction, the VCG auction. We analyze the findings of each of the extensions concerning all the performance indicators in the subsequent sections and present the details of the trucks' earnings and packages waiting times in the end.

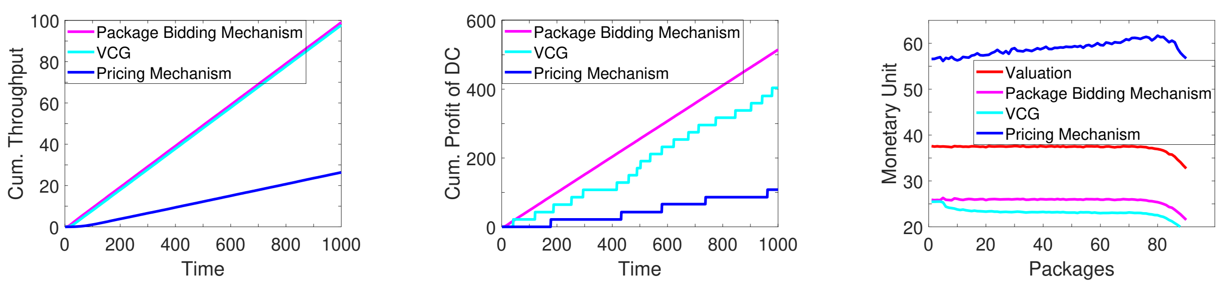
5.1 Capacity of Trucks is Common Knowledge

In this section, we assume that the trucks indicate their capacity to the DC, and the DC makes this knowledge public. So, when the packages arrive, in addition to observing the number of other packages and waiting time, they also observe the capacity of the trucks. Since the bids are offered in the increasing order of distance from the DC, they initially bid according to the capacity of the nearest truck and subsequently bid according to the capacity of the truck to which the bid is being offered. This essentially takes the form of a uniform price auction. Since each package requires unit space, the optimal bid is to bid truthfully. The truck accepts the packages based on their capacity and the packages have to pay the market-clearing price. The market-clearing price here refers to the lowest of the bids selected by the truck in the load bid (Krishna 2009). The only difference between this extension and our main analysis is that there is more credible information available to the customers. Hence, we can interpret this extension as evaluating the value of information. We can see from Figure 3 that, on expectation, the first-price auction with no information on capacity coincides with the uniformprice multi-unit auction with capacity being common knowledge and outperforms the platform pricing mechanism. This is an interesting result, because these two auction formats are different and first-price auctions are not always efficient, whereas the uniform price auction for unit demand is always efficient (Krishna 2009). However, the reason that they produce almost similar results is because of the high number of incoming and participating packages. We know that the optimal bidding strategy for the first-price auction is to shade bid, $\frac{n-1}{n}v$, where n is the number of other packages and v is the valuation, and for a uniform price auction with unit demand is to bid truthfully, v; thus, as n increases, the optimal bids start converging. Since the truck's decision process remains unaffected, the results of both these formats coincide in expectation.



(a) (b) (c)

Figure 3: Capacity common knowledge: (a) cumulative throughput at DC, (b) cumulative profit of DC, and (c) amount paid by the customer.



(a) (b) (c)

Figure 4: VCG auction environment: (a) cumulative throughput at DC, (b) cumulative profit of DC, and (c) amount paid by the customer.

5.2 VCG Auction

In this extension, we keep assuming that the capacity of the trucks is common knowledge and use an extension of the second-price auction, the VCG auction, owing to the established results that the VCG auction is efficient, produces socially optimal results, and induces truthful bidding (Vickrey 1961; Clarke 1971; Groves 1973) and for the sake of completeness. We can see from Figure 4 that the throughput at the DC is significantly higher than that of the platform pricing mechanism, but slightly lower than the package bidding mechanism. The profit of the DC, under VCG, is lower than the profit under the package bidding mechanism and higher than under the platform pricing mechanism. Finally, the actual amount paid by the packages is the lowest of all mechanisms and significantly lower than their valuations. Table 2 enumerates and quantifies these results. The results can be ascribed to the algorithmic design of VCG auctions. Since the VCG auction mechanism inherently recalculates and redistributes the bids, eventually charging individual bidders the harm they cause to other bidders (Cramton, Shoham, and Steinberg 2006), akin to the Shapley value but with opposite intent (Shapley 1953), the packages end up paying less than their valuations, thereby reducing profits at the DC. From Table 2, we see that both the trucks and the DC prefer the package bidding mechanism to the VCG mechanism. However, the customers prefer the VCG mechanism over the package bidding; all three agents prefer VCG to the platform pricing mechanism.

Table 2: Performance of VCG auction environment.

Performance Indicator	**VCG Auction**	**vs. Package Bidding**	**vs. Platform Pricing**
Cumulative Throughput at DC	100 packages	$\downarrow$ 1 %	$\uparrow$ 400 %
Cumulative Profit of the DC	402 monetary units	$\downarrow$ 34 %	$\uparrow$ 300 %
Amount Paid by the Customer	23 monetary units	$\downarrow$ 11 %	$\downarrow$ 60 %
Number of Active Trucks	21.0773	$\downarrow$ 5 %	$\uparrow$ 300 %
Earnings of Trucks	87.45 monetary units	$\downarrow$ 6 %	$\downarrow$ 0.3 %
Package Wait Times	31.603 ($\pm$ 22.386) time units	$\uparrow$ 90 %	$\downarrow$ 86 %

6 CONCLUSION AND DISCUSSION

Motivated by the lack of success of on-demand service firms in the logistics sphere, we propose an alternative mechanism that serves to address the potential shortcomings of the status-quo pricing mechanisms, i.e., platform pricing. In the platform pricing mechanism, the platform manipulates the demand and supply by setting appropriate prices and wages, for both sides respectively, while maximizing their profit. Since the customers are price takers, their participation is constrained by the price set by the platform, which means that packages that do not derive a positive utility from the system, choose not to participate. However, we propose a mechanism, motivated by auction theory, where the packages bid their willingness to pay to get service. In this case, instead of being constrained, all the packages participate, because there exists a positive probability that they will get service for the amount they are willing to pay. Although this mechanism serves to focus primarily on the packages, we also analyze the impact of the said mechanism on the trucks as well as the DC. From the point of view of trucks, this mechanism is a means to complement their existing operations by allowing them to utilize their capacity more efficiently while enhancing their earnings. We find that the package bidding mechanism outperforms the platform pricing mechanism significantly across all performance metrics, and proves to be beneficial for all three agents. Having established the better performance of the package bidding mechanism, we extend our analysis to two different types of auctions, Uniform Price Auctions and VCG Auctions. We find that, in the long run, the uniform price auction is indistinguishable from the first-price auction; also, the packages prefer the VCG auction format, while the DC and the trucks prefer the first-price auction.

In this paper, we analyze a stylized and simple model to gain insights into the efficacy of our proposed mechanism. However, this results in abstracting away from many operational details. For example, we analyze a single DC, whereas, in real life, a DC is almost always a part of a larger network. Thus, it would be interesting to conduct a similar analysis for a network of DCs, evaluate how our mechanism performs, and especially pay attention to whether or not the agents try to game the system, e.g., by colluding. Also, in this paper, we focus on the ordinal performance of our mechanism, it would be more rigorous if we normalize and scale the parameters to reflect real-life values and, then, analyze the ensuing outcomes. For example, we could normalize and scale the valuation, weight, and distance to a single parameter, $\frac{v}{MD}$, which signifies the ratio of valuation and requested service units. This parameter warrants further analysis because, intuitively, a high valuation package with low service units demand might prefer the platform pricing mechanism, because otherwise it would have to bid and potentially pay a high amount owing to its high valuation. Also, it would be interesting to analyze the impact of holding cost at the DC, because that would implicitly place an upper bound on the time a package can spend at a DC waiting for service.

A NUMERICAL EXAMPLE

Here, we provide an illustrative numerical example detailing the steps of our simulation process. We use the same numerical values as in Section 4.1 for all the problem parameters except K and initialize our simulation by generating the random variables as well as deterministic components; for this numerical illustration, we use $K = 10$. The first 3 packages arrive at the following time units, $\{0.2, 15.43, 16.83\}$ and their v, m, and d are $\{46.45, 36.963, 25.69\}$, $\{5.804, 8.54, 6.73\}$, and $\{0.13, 12.21, 2.17\}$, respectively. At this stage, system utilization and W_q are 0.2 and 0.552, respectively. Under the platform pricing mechanism, solving the constrained optimization problem from Section 3.4, the platform calculates the optimal per-unit price and quotes the packages $\{1076.6, 18.2, 78.8\}$ monetary units. The first and third packages derive negative utility from the quoted price and leave the system. However, the second package derives a positive utility from the quoted price and is matched with one of the active drivers. Under the package bidding mechanism, within a first-price auction environment, the packages bid $\{29.13, 22.80, 15.28\}$, following the shade bidding strategy in Section 3.5. The lower bound on the trucks' outside option is 80, and hence, irrespective of the availability of capacity, none of the trucks accepts any of the packages' bids. The fourth package arrives at 18.0202 with the following v, m, and d, $\{38.05, 6.6, 3.4\}$ and W_q changes to 0.78. Under the platform pricing mechanism, this package is quoted a price of 53.02 which translates to a negative utility leading to the package leaving the system. Under the package bidding mechanism, all the packages update their bids to $\{31.89, 24.77, 16.32, 25.59\}$. At this stage, none of the active trucks has a capacity of more than two units. Hence, none of the packages is picked. The fifth package arrives at 42.12 with the following v, m, and d, $\{46.4, 5.14, 2.07\}$ and W_q changes to 0.67. Under the platform pricing mechanism, the package leaves the system owing to a negative utility. Under the package bidding mechanism, the updated bids are now $\{37.31, 34.47, 27.75, 26.88, 17.86\}$. The nearest truck has a capacity of two units and an outside option of 92.3. Since no combination of two bids is more than 92.3, the first truck does not pick any package. However, the second closest truck has a capacity of five units and an outside option of 118.7. This truck accepts all the packages and leaves the system for the service duration. We continue the process for a given time and replicate it to get the long-run averages. For the extensions, the process is similar with the only difference being the optimal bidding strategy owing to different auction environments.

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