Optimization Models for the Procurement through Reverse Combinatorial Auctions in the Logistics and Food Industries

C. Triki[1,2,*], J. Akil[3], H. Al-Asmakh[1]

[1] Division of Engineering Management and Decision Sciences

College of Science and Engineering, Hamad Bin Khalifa University, Doha-Qatar

* Corresponding Author: ctriki@hbku.edu.qa. ORCID: 0000-0002-8750-2470

[2] Department of Engineering for Innovation, University of Salento, Lecce-Italy

[3] Department of Natural Resource Economics, Sultan Qaboos University, Oman

Abstract: Procurement managers in the different industries rely nowadays on the Reverse Combinatorial Auctions (RCAs) as a trading mechanism that have shown to be very efficient in allocating resources in several applications. RCAs allow the bidders to optimally express their economies of scope, since they can formulate their bids as a bundle of items, rather than on single item. Each bundle should be then either accepted or rejected all together without splitting. Here, we review and discuss the underlying mathematical optimization models that represent the basis of the decision support system and discuss the possible benefits of using such paradigms for the different actors involved in the auctioning process. In addition the paper highlights the advantages of employing RCAs in two major application fields, namely the logistics and food industries, in which this advanced trading paradigm had remarkable success by allowing the bidders to exploit better the synergies among the auctioned items and concede the auctioneers to minimize their procurement costs.

Keywords: Combinatorial auctions; bid generation; winner determination; logistics procurement; food industry; optimization models.

3. Introduction

The aim of our study is to highlight the feasibility and advantages of designing and running internet-based markets for the e-procurement of multi-item goods or services. The considered market will use combinatorial auctions as a trading mechanism (Vangerven, 2017) rather than (or in parallel to) the traditional techniques based on tendering and negotiations. RCAs have shown to be very efficient in allocating several kind of resources in a wide range of industries. A non-exhaustive list include the electricity trading in restructured power markets (Triki et al., 2005; Musmanno et al., 2010) telecommunications service obligations (Kelly and Steinberg, 2000), phone spectrum licenses (Gunluk et al. , 2005), harbor time slots (Ignatius et al., 2014), mineral and oil drilling rights (Cramton, 2007), real estate (Goossens et al., 2014), and Construction

Procurement (Al Shaqsi, 2018). Earlier, pioneering applications included the airport runaway timeslots allocation (Rassenti et al., 1982) and revenue management for the treasury bills trading (Menezes, 1995).

In recent years, an increasing importance of using RCAs is being given to two industrial sectors: logistics and food procurement. In both fields, the scientific literature has reported several successful experiences of companies that resorted to the use RCAs in order to procure goods or services with the aim of achieving cost savings (Milgrom, 2004). Bidders can also take advantage from their participation in the e-auctions by bidding on bundles of items, rather than on several single items separately, with the aim of taking advantage from their economies of scope. This latter term means, in the context of RCAs, grouping a subset of the items within the same bundle for the sake of increasing the synergy among those items and achieving further advantage by winning them together as a package. Moreover, in some industries the bundling feature in RCAs helps the auctioneers not to split their procurement from too many suppliers and to encourage the bidders to focus mainly on coarse bids that can remarkably increase the value of their business.

Depending on the auction rules, bidders can take advantage of the flexibility of expressing their bundles in a complex way. For example, bidders can submit sealed bids involving inclusive or exclusive statements such as "I am interested in items A and B together and willing to pay price P_{AB} for both, or none" or "I am willing to get items A, B & C together at price P_{ABC}, otherwise item D alone at price P_D". They can also increase their chance to gain as much new business through auction as possible by submitting even overlapping bundles such as "I submit bid-1 involving items A, B & C at price P_{ABC}, and also bid-2 involving items A & C at price P_{AC}". This means that any bidder can typically generate a huge number of possible bids (that can amount to $2^N - 1$, where N is the number of items put for auction), a fact that makes the task of generating the most appropriate and most profitable set of bids to be submitted to the auction an extremely difficult optimization problem (Cramton et al., 2004). Such a problem is known in the scientific literature as the "Bid Generation Problem" (BGP). Likewise, the auctioneer will be faced with another very complex model, called the Winner Determination Problem" (WDP), that has the role of identifying the winning bids and assigning the items to the successful bidders (Sandholm, 2000). The complexity of the WDP is due, from one side, to the high number of, even conflicting, bids submitted by the bidders and, from the other side, to the necessity of incorporating complicating features that allow expressing the auctioneer preferences. One of those features that can have particular impact on the WDP complexity is the criterion of selecting the winning bids that can be based on the first - or second-lowest-price sealed bid (Blumrosen & Nisan, 2007, Watts, 2018, Karaenke et al., 2019). Besides these two widely studied problems, we should define a third optimization model, called the "Item Selection Problem" (ISP), in which the auctioneer needs to determine the set of items to be auctioned off and those to be ensured by a different trading mechanism (for example through bilateral contracts). All these problems and the interaction among them in the context of RCAs are shown in the general framework depicted in Figure 1 (see also

Triki, 2016). In the next sections we will give examples of such optimization models to be solved by the different actors involved in the three phases of the auctioning process with particular focus on the logistics and food industries.

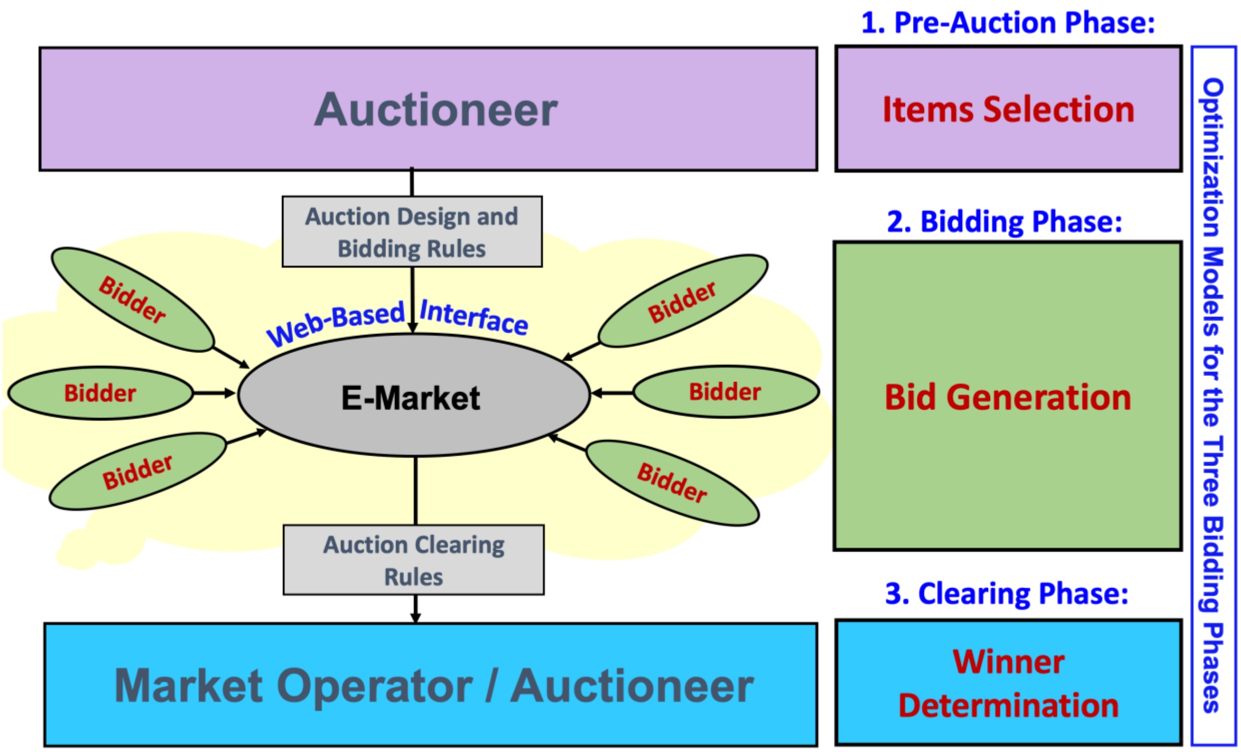

Figure 1. Optimization problems within the auction mechanism

The kind of auction we are considering in this review is the reverse auction, that involves one single buyer, as auctioneer and several sellers, as bidders. This auction design results to be particularly suitable for the applications we are dealing with in this paper with respect to its one-seller-many-buyers counterpart, called forward auction, widely used for the trading of goods such as art pieces, fish, real estate, etc. Yet, a more general kind of auction involves multiple sellers and multiple buyers and is known as multilateral or two-sided auction (such as Ebay). All these kind of RCAs are generally run online through internet in order to enhance the negotiation security and reduce the transaction time and can consist in either one or multiple rounds. In the single round auction the bidders will submit their bids only once followed by the auction clearing to decree the winning bidders. On the other hand, the iterative auction will be run as multiple bidding/clearing rounds in which the bidders can adjust, after each round, their bidding price in order to react to the clearing outcomes. The iterative process is stopped only when none of the bidders is willing to make any change to their bids.

It is worthwhile noting that the combinatorial auctions are one of the most advanced auctioning format as compared to other traditional auctions such as the sequential and parallel auctions. In the former format, the items are auctioned one at a time and in the latter all the items are available for bidding in parallel (Cramton et al., 2004; Sandholm, 2000). However, none of these auctions ensure to protect the bidders against the so-called exposure problem and that consists in failing to win some of the items that exhibit strong complementarity with other successful items. From this point of view, the all-or-nothing bidding rule within the RCAs represents a key advantage for the bidders who want to avoid any risk of winning only part of the items that are characterized by a high level of synergy and that can have value only when obtained together as a bundle.

It is to be noted that most of the models introduced in Figure 1 will be often characterized by a stochastic nature since many of the problems' parameters (cost, demand volumes, etc.) are not known with certainty in advance. Consequently, we will not limit our interest here only to the deterministic models developed for both industries, but we will also review the stochastic variants of the models, whenever they are available.

The aim of this study is to provide a guideline on the optimization models that need to be defined and solved by the different actors in order to ensure their efficient participation in the auctioning process. This review will help the researchers in understanding the modelling challenges arising in two important industries and will support the practitioners with efficient decision support tools to enhance their experience in fruitfully participating in auction-based businesses. The paper is structured as follows: Sections 2 and 3 will be dedicated to the optimization models so far developed in the fields of transportation and food procurement, respectively. While we follow an approach based on focusing on the optimization models arising in RCAs in Section 2, we will focus on reviewing the few case studies available in the food industry in Section3. Finally, Section 4 will conclude the paper and will give some insights on research gaps in the scientific literature.

2. Applications of RCAs in the Transportation Procurement

Transportation companies are often faced to many challenges while trying to efficiently serve their customers. It is widely accepted that firms aiming to service customers scattered in a vast area should possess an efficient service plan to save time and money. Freight transportation is considered as the largest logistics expense for a vast number of industries and it is, thus, the area where significant savings can be made (Ghiani et al., 2013). Therefore, a large number of companies are trying to achieve high levels of reliability, flexibility, and agility in their transportation systems in order to fulfill customers' demands. An efficient approach is to consider RCAs as an option instead of relying only on the companies' own fleet or on forward contracts with third- and forth-party logistics providers (Huang and Xu, 2013). The literature reported real-life experiences that succeeded to achieve up to 15% of transportation cost cutting after implementing RCA solutions.

The items to be auctioned off in this context are transportation contracts, i.e. a load or a contract having a certain volume to be moved from an origin to a destination. In the sequel, we will review the scientific contributions in the field of transportation procurement by subdividing them into the three auctioning phases, as per the general framework shown in Figure 1.

2.1 Pre-auction Phase: ISP Models

Large shippers usually cover part of their transportation needs by using either their own fleet or through forward contracts with third- and forth-party logistics providers (Attanasio et al., 2007). With the advances achieved in designing and running RCAs, the shippers can also take advantage of this new trading mechanism. In the pre-auction phase, the shipper will try to identify the transportation needs (contracts and called also lanes) to be served by his own fleet and those to put into auction as contracts. Then, the shipper will invite carriers to bid on the auctioned contracts. Basically, the problem in this stage consists of identifying and selecting the contracts, out of many, that will be served by the shipper's own fleet and in organizing an auction for the others. This problem is known as the Shipper Lane Selection Problem (SLSP). It needs to be solved by companies (called buyers) such as manufacturers, distributors and retailers that need to move their goods around a logistics network. On the other hand, all trucking companies or carriers could be potential sellers. To the best of our knowledge the SLSP has been subject to only few research works. The first is due to Guastaroba et al. (2009) in which the authors limited their horizon interest to one single time period and have proposed two different optimization models. The second work was advanced by Triki et al. (2017) who considered an extended time horizon to cover a multi-period planning environment and suggested an integer programming formulation. Moreover, the authors proposed three metaheuristic approaches for its solution. The last work we are aware of was developed by Triki et al. (2020) in which the SLSP model has been embedded within a production-distribution framework while involving occasional drivers that contribute in accomplishing part of the delivery tasks. Their study has shown that the SLSP can gain efficiency, expressed in terms of total cost minimization, by coordinating the production and delivery activities. For the purpose of validating the developed models and comparing the performance of their approaches, all the above works have used a set of properly adapted test problems based on the well-known Solomon's library (Solomon, 1988).

A typical SLSP model should have the following structure:

Min (Routing cost of serving a subset of contracts through the own shipper's fleet) +
(cost of outsourcing a subset of contracts through auction)
s. to:
Constraints that define feasible routes for the self served contracts
All the contracts will be serviced either directly by the shipper or through auction
All variable related to the routing of the own fleet should be binary
All variable related to auctioning (or not) each contract should be binary.

The above model turns out to be an integer programming model whose size increases quickly with the total number of lanes/contracts to be served and with the number/nature of vehicles. Moreover, the problem can become even more complex by incorporating additional variables and/or constraints that allow to extend the planning horizon to cover a multi-day period or to include other logistics tasks, as suggested in the above works.

2.2. Auctioning Phase: BGP Models

In this phase of the auctioning process, the invited carriers will determine their bidding strategy in terms of defining the bundles of contracts on which they want to bid and their corresponding bidding price. Thereafter, they will submit the bids to the auction and wait for the clearing results. The early works in this contexts have dealt only with the bundles generation (i.e. pure BGP) without bothering about determining the bidding price that was left to be calculated based on commercial considerations. Later on, scholars and practitioners have recognized the importance of jointly defining the bundle and its price by solving the bid generation and evaluation problem.

Caplice and Sheffi (2003) argued that it is better to allow carriers identifying packages on the basis of their own perspective and network since shippers specified packages turn to be less successful for transportation. Song and Regan (2004) developed optimization-based approximation algorithms for solving the BGP under two scenarios, with and without presence of pre-existing commitments. Several limiting assumptions have been made such as the absence of a central depot and the unlimited carrier's capacity. Further, Song and Regan (2005) proposed a two-phase strategy to tackle a truckload (TL) vehicle routing problem in order to generate bids. The approach used a set-partitioning algorithm to determine the desirable bids. Given the pairwise synergies within a bid, An et al. (2005) proposed a model to assess the bundle values. They also developed bundle construction algorithms for selecting profitable bundles. Similarly, Lee et al. (2007) proposed an optimization model integrating simultaneous generation and selection of routes, and maximizing the profit deriving from the most profitable bundle. Their optimization model is based on the trade-off between repositioning cost versus rewards associated with serving contracts. Chang (2009) proposed a decision support model for the carriers participating in one-shot RCAs. His bidding model integrates the load information in the e-marketplace with the carrier's fleet management plan and chooses the desirable bundle of loads. Later on, several decision tools that allow to generate bundles to be submitted to RCAs have been developed based on the concepts of: synergy among the contracts (Triki, 2016), heterogeneous truckload operations (Hammami et al., 2019), considering the carriers collaboration (Mamaghani et al., 2019), minimizing the delivery lead time (Mamaghani et al., 2019), and in-vehicle consolidation (Yan et al., 2020).

The literature survey shows that few other works have developed optimization models for the long-haul full truckload transportation service in stochastic and fuzzy settings, such as Triki et al. (2014) and Kuyzu et al. (2015). Both works have considered the bidding price as an uncertain parameter of the problem and the former work has integrated even the routing decisions within the same

optimization framework. Recently, Yan et al. (2018) have formulated the BGP as a bi-level optimization model and used the fuzzy descriptor for the representation of the problem's uncertain input data.
A possible textual description of the BGP model can be summarized as follows:

Max (Revenue from acquiring new transportation business) –
(Total routing cost involving the new business won through auction)
s. to:
Constraints that define feasible routes (path continuity, no subtours, etc.)
Only a given number of bundles should be generated among the possible ones
Offered price for each bundle ≤ Price submitted by all other competitors for that bundle
The deliveries belonging to the successful bundle should be included in the routing plan
The variables associated with the price of the submitted bundles are non-negative
The variables associated with the selection/non-selection of any bundle belong to {0,1}

The BGP's objective consists of maximizing the net profit behind participating in the auction. Specifically, the bundles to be selected should ensure enough gap between the revenue deriving from serving the deliveries won through auction and the extra-cost deriving from serving those new deliveries.

2.3 Post-auction Phase: WDP Models

This last phase consists of solving the WDP to be solved by the shipper just after the deadline of the bids submission. The WDP will select and assign the successful bids to the carriers on the basis of some cost minimization criteria. While this problem has been extensively investigated in different application contexts, it received only a limited attention in the transportation sector (De Vries and Vohra, 2003). In the deterministic settings, Caplice and Sheffi (2006) proposed different optimization models for the WDP for truck-load transportation auctions. Ignatius et al. (2014) proposed three different multi-objective optimization models to address the WDP. The work demonstrated, through the use of sensitivity analysis, that the shipper could use different options depending on the given situation while awarding the contracts. Moreover, specialized models have been developed for real-life applications such as those reported by Ledyard et al. (2002) and Elmaghraby and Keskinocak (2003). Triki et al. (2020) defined and solved the WDP for a manufacturer when his production scheduling problem is embedded with the delivery planning within an integrated model. In a similar context, Lee et al. (2020) defined a WDP for the auction clearing in a scheduling-routing of automated guided vehicles related to warehousing applications. In order to overcome the difficulties of solving a complex mixed-integer model, they developed a Genetic Algorithm approach that uses knowledge based operators.

The research on the WDP has also been directed towards solving the problem under uncertain parameters. Ma et al. (2010) suggested a recourse stochastic model incorporating the volumes of the good to be transported. Remli and Rekik (2013) proposed a recourse robust model to include the stochastic nature of the shipment quantities. They also presented a constraint generation algorithm for its solution. Zhang et al. (2014) suggested a sampling-based algorithm that includes a Monte Carlo method to generate the scenarios representing the uncertainty within the WDP. Later on, Zhang et al. (2015) incorporated the randomness related to shipment volumes by using a robust optimization approach with recourse decisions and developed a data-driven method for its solution (see also Devanur et al., 2019 for the online RCA case). Remli et al. (2016) extended previous works by incorporating within their model, not only the stochasticity of quantities to be delivered, but also the randomness characterizing the carriers' fleet capacity and delivery lead times. Recently, Qian et al. (2020) proposed a 2-stage WDP that takes into account the possible disruption risk of bidders' service and allow for fortification, reservation and outside option policies as a recourse action.

A general formulation of the WDP within the RCAs framework can be given as follows:

Min	Total price of successful bids over those submitted by all bidders
s. to.	
	Every contract is assigned only once
	All the contracts belonging to each bid should be entirly accepted or none
	The decision variables (bid accepted/rejected) should be binary

The outcome of the WDP consists of a 0/1 value of every binary decision variable that identifies if each bid is selected to be a winner or not, whereas the objective value will represent the total price to be paid by the auctioneer to the bidders based on their bids' suggested prices. It is worth noting here that the WDP may need to involve additional side constraints depending on the specific bidding languages that will be employed during the auction design (see Abrache et al., 2007).

3. Applications of RCAs in the Food Industry

The following section will highlight the main aspects of applying RCAs in the context of food industry. We will discuss the motivations behind employing auctions, the most appropriate kind of auctions to be designed, their advantages/disadvantages and the types of models to be designed. It is to be noted that the number of works dealing with the employment of RCAs for the food industry management is not as high as in the case of transportation procurement. For this reason, our review in this section will be applications-oriented rather than auctioning phases oriented. Indeed, we will discuss in the sequel three different real-life applications along which we will describe examples of the arising optimization models. Yet, our focus here will be devoted to only the procurement aspects in the food industry and will, thus, ignore other applications that results to be out of this study's scope, such as the intra-enterprise exchange of logistic services (Gujo and Schwind, 2007) or the employment of RCAs for the food service layout design as described in (Fujii, 2020).

3.1. Application of Auctions at Mars Food Inc.

Mars Incorporated is considered as one of the leading American global manufacturers, specialized in food, beverages, pet care, etc. Given the large range of products and services it manages, Mars uses a variety of buying techniques to deal with different purchasing scenarios. The most common purchasing technique used at Mars is sealed bid tendering and traditional negotiations. Even though these methods are widely used, they have some disadvantages such as not being able to ensure full transparency and do not allow the buyers to benefit from the economies of scale for some specific areas of production. Moreover, conventional negotiations usually force the buyers to devote a significant amount of time for price and quantity discussions, which can be done more effectively through online auctions. Therefore, in the early 2000s when online reverse auctions became widely popular as an efficient tool for procuring and managing negotiations, Mars decide to adopt and take advantage from such new tool (Hohner et al., 2003).

Even though RCAs enable buyers to procure products and services in a cost effective manner, they can negatively impact the buyer-supplier relationship since they focus heavily on price. In addition RCAs often create a challenging setting for buyers to limit the traded volumes and number of awarded vendors. Hence, the design goals of the auction was to support Mars in conducting strategic procurement, with a focus on having a small supply pool and maintaining long term relationships with suppliers. In order to achieve this, Mars ran combinatorial auctions with commitment on both sides using an iterative auction format. The objective of the Mars, as a buyer, is to reduce the total cost of ownership while following specific business rules imposed by Mars. For the sake of avoiding the reliance on a limited number of suppliers, Mars required the number of awarded suppliers to be above a specific minimum threshold. On the other hand, to avoid the burden of managing a large number of suppliers, the number of awarded suppliers is bounded by a maximum value. Furthermore the value awarded to each supplier is limited to a specific amount in order to restrict the exposure to a single or a limited number of sellers.

This combinatorial and iterative nature of this auction is advantageous for Mars with respect to other auctions, as it enables the sellers to bid on a bundle of items they are interested in selling and re-submit their bids if they were noncompetitive in the previous round or were submitted by fault. Suppliers are requested to offer a single price for a bundled bid of their choice. Each auction iteration runs for an average of one hour, but Mars can decide to slightly extend the bidding time if needed. Given the complexity of the bidding structure and Mars's business rules, the developed winner determination problem is considered to be NP-Hard. Therefore for every bidding round, an integer programming formulation including Mars's business rules as side constraints, is used for clearing the auction and determining the winning bids. The optimization engine to solve the WDP was first designed in C++ as an independent software module and later on it was incorporated into a web-based online auction platform. The buyer can, through the WDP model, identify the specific quantity of units to be procured for any given item (referred to as lots). It can be represented verbally as follows:

Min Total Bids prices offered by all sellers for the offered amount of lots s. to: The pre-defined quantity required by the buyer must be fulfilled for each item The total quantity to be awarded to each supplier is bounded by lower/upper bounds Limit the total number of awarded suppliers to be within a pre-specific range Ensure that the binary variable to set to 0 if the supplier is not awarded any lot

Even though Hohner et al. (2003) case study does not report detailed numerical values regarding to the outcome of this auction employment compared to other procurement methods, the authors noted that the employment of RCAs resulted in a consistent cost saving and a significant Mars's margins improvement. Mars's online auction website "Number1traders" succeeded to regularly yield remarkable cost cutting and positive savings, which encourages the company to intensively adopting the RCA mechanism. In addition, even Mars's suppliers were supportive to this tool as they appreciated its level of transparency and the added control that RCAs provided them. Finally, the paper reports another positive aspect of this application which consists in estimating the return on investment for designing and developing Mars's auction platform was generated in less than a year.

3.2. Application of Auctions for the Meals Distribution

Throughout every school year in Chile, the governmental agency *Junaeb*, valued at a procurement cost of three billion dollars, has to provide two and a half Million students with two daily meals. For thirteen years, the contracts were awarded through the same approach of sealed bid single round combinatorial auctions (Olivares et al. 2012). The competition between suppliers is mainly focused on pricing, since the meal services are standardized. The use of combinatorial auction is driven by the division of Chile into 100 school districts, which allows suppliers to bid on any bundle including one or more districts according to their capabilities.

The tendering process is performed though an online system, where bidders go through a prequalification phase based on their managerial and financial competences. The number of suppliers partaking in the tender is around 20, with each supplier submitting bids ranging from hundred to thousand for one or multiple locations. Winning suppliers are required to run the whole supply chain in the awarded district, beginning from procuring raw food components and then preparing, distributing and serving the meals in each school. Suppliers are allowed to bid on any preferred combination with a maximum of eight districts in order to encourage competition. The package bids are then either entirely accepted or declined. The goal of the buyer (i.e. Junaeb agency) is to identify a combination of bids that covers all of the locations in a cost-effective manner. In a similar way as the model presented in the previous sub-section, the WDP is formulated as an integer linear program and considers too a set of constraints purposely designed by Junaeb agency.

Concerning the design of the RCA, the agency has decided to implement a single-round, sealed-bid and first-price auction. Two main issues can arise with such design components and that will heavily influence the bidding behavior of the suppliers. That is, which and how many bid bundles should be allowed and how to diversify the suppliers base. Considering the first issue, it is argued that providing suppliers with too much flexibility of bidding on any possible combinations, can negatively impact the efficiency and increase the procurement total cost if sellers leverage the package bidding process. Therefore, the agency enforced that the bidding structure should restrict the possibility for bidder to bid only on bundles involving districts where cost synergies are appropriately significant. For this purpose, Junaeb considered two types of synergies including the economies of scale (that depend on the number of meals to be served) and economies of scope (that reflect the synergies related to the logistics and transportation costs).

As for diversifying the supplier base, the bidding structure designed by the agency imposes several restrictions on the distribution of districts among the sellers. Among these, the maximum number of districts that each firm can be allocated should range from two to eight, depending on the financial analysis performed appointed to each supplier. Another restriction that enhances competition is that the total number of contracts awarded to any supplier should be bounded by 16% of the total number of meals in all districts. Furthermore, a local market share constraint is imposed to limit the number of districts a supplier can be awarded within any specific geographical district and, finally, an additional rules requiring a minimum of around 10 firms to be involved in the allocation of each RCA.

Olivares et al. (2012) reported that the researchers verified a-posteriori the effect of these restrictive rules on the bidding/clearing process. For this purpose, they collected data related to all bids submitted along seven years. Their analysis highlighted that by eliminating all the design restrictions related to the market share will not result in any improved outcomes. Indeed, the solution of the pure WDP (i.e. involving the same submitted bids but without market share constraints) shows that, even though the optimal bundles assignment often changes, the cost of meals procurement increases by only 0.3% on average. Some additional insights gained from such a-posteriori analyze is that: (i) large companies usually submit larger bundles but, in the same time, they limit the number of their bids to only six bundles average; (ii) most firms use volume discounts in their bundled bids even if no cost synergies can be observed; and (iii) small firms succeed to be competitive and to gain business even without market share impositions.

The paper develops also an econometric model that allows estimating the bidding price defined as the price per meal divided by the number of meals for the set of districts submitted as a bundle by a specific seller. This is a kind of BGP model, that has the role of supporting the sellers in defining their bidding strategy. The bidding price is defined as the difference between two components: the value of the items within the packages and the discount function related to any specific package. Its mathematical formulation can be textually expressed as follows (Olivares et al., 2012):

$$\boxed{\begin{aligned}&\text{Bid price} = \text{ Summation over bundeled districts [average unit price in a district} * \\ &\qquad \frac{\text{District Size (\# meals in a certain district)}}{\text{Bundle Size (total \# meals in the bundeled districts)}}\text{] – Discount Function of the bundle}\end{aligned}}$$

The unit cost in the above formulation is impacted not only by the size and location of schools where the meals will be served, but also any other specific benefit the supplier may have such as being near a warehouse which enables him to charge a lower price. Furthermore, some bidders may be able to charge a lower unit price due to ongoing contracts with nearby districts from previous auctions (that that can reach 2.3% on average). As per the discount function, it depends, as highlighted above, on the level of synergies that every bundle exhibits and takes into account the scale discount (based on size of the bundle) and the density discount (based on geographic districts covered by the bundle).

3.3. Introduction of the Electronic RCAs to a Food Manufacturer

A processed meat manufacturer in the United States introduced the RCA mechanism in its tenders to encourage competition and reduce the cost of procuring sweeteners across eight plants (Harris et al., 2014). Corn sweeteners are considered to be of low cost due to their high demand. However, in 2006 the cost of sweeteners increased due to a change in the demand trends. Therefore, the food company was looking for alternative procurement methods to maintain their profits. One of the many advantages of combinatorial auctions in this context is that it allows sellers to bid on bundles of sweeteners and plant locations based on their production and delivery capabilities. However, RCAs can also make the bid evaluation process more complicated, specifically when non-quantitative attributes, such as flexibility, should be considered. Therefore, the manufacturer's procurement department conducted an analytical comparison and decided to consider two different auction designs: the single items sealed-bid reverse auctions and the multi-item combinatorial reverse auctions involving bundled bids. The final choice will be based on the real-life experiments on both the auctions.

The initial tendering process prior to the introduction of the reverse auction was based on standard mail correspondence between the buyer and the sellers. The company classified purchases based on two factors: the direct inputs which are related to raw material of the product and the indirect inputs, like repairing and maintenance services. The indirect inputs have more frequent transactions and a their total cost is higher than the direct inputs. In order to reduce the indirect input costs, the company initiated an e-procurement method that includes an agreed on the price list and a catalog of products for buyers to choose from. For direct inputs, the food company uses manuals or electronic auctions to ensure that the communication between the buyer and sellers is as efficient and fast as possible.

The bidding event was held on a website developed by a third party service provider, where buyers and sellers were able to communicate. Sellers were required to attend an online training to practice the navigation of the tools on the website. It included nineteen bidding scenarios for single bids and 100 different bid combinations for the bundled bid format given the four types of products (dextrose, corn syrup solid, corn syrup and liquid dextrose) and 8 plant locations across five different US states. The suppliers were able to choose which bidding format to adopt based on their preferences since both auction formats were conducted simultaneously for a duration of four hours.

By running both the auction designs during one whole year the manufacturer was able to draw the following important findings: when the single-item bids auction is applied, only two suppliers were able to meet the requirements of supplying the entire volume of sweeteners. On the other hand, when employing the bundled bidding auction, the number of placed bids increased by 54% with respect to the single-item auctions. Therefore, suppliers were able to cover the buyer's demand more efficiently due to the lower number of constraints imposed on them. Finally, the results reported in Harris et al. (2014) highlighted that both the auction designs achieved important savings with respect to the national market prices during the same experiments year and that the RCA succeeded to achieve around 5% profit benefits compared to the single-item bid auction.

4. Conclusions and Research Gaps

Most of the companies that experimented and run RCAs for the e-procurements of their goods or services have reported significant reductions in their shipment costs (see the RCA software developer "ariba.com" web page). Moreover, bidders can achieve high levels of efficiency by submitting bundles of items that take into account the synergies they have among the different auctioned items. Furthermore, the facilities offered by the internet that allow implementing online RCAs open the door for the creation of new companies that can provide valuable know-how, products and services to the local markets. All these advantages often result in positive impact on the whole supply chain and in an improvement of competitiveness of the overall economy.

Despite the several advances achieved in the field of RCAs, there are still some research gaps that still need attention. Further investigation in this field will contribute in increasing the efficiency of applying RCAs in real-life applications and will convince more practitioners to take advantage from this paradigm. We should specify that these gaps are not application-oriented but are devoted to the techniques of designing and running RCAs:

- First, we mentioned above that the number of possible bundles that can be generated in any RCA can be extremely high because it increases exponentially with the number of auctioned items. For example, it would be prohibitive to include all the potential bundles within a GBP in order to generate the most attractive bids. Thus, one way to reduce the negative effect of such curse of dimensionality is to develop some preprocessing procedures that can reduce the number of bundles by eliminating a-priori all non-promising ones.
- Second, we highlight along all the paper the important role that the synergy among auctioned items plays in defining efficient bundled bids. However, one can find in the literature very few works that attempted to define quantitative methods for the approximation of the synergy level among items (An et al., 2005; Triki, 2016). Moreover, to the best of our knowledge, there are no studies that develop optimization models that can optimally select the bids on the basis of the synergy existing among a sub-set of items.
- Third, despite there are some works that incorporated the stochastic aspect of the input parameters within the BGP or the WDP formulations, this field is still considered in its infancy and many advances are expected in the coming decade. For example, most of the contributions considered the bidding prices as independent random variables and introduced, in the best scenario, corrective approaches to deal with the items price dependency. However, it is well known that the price of an item often depends on the set of other items with which it is bundled. Another avenue of research in this context consists in employing the multi-stage recourse stochastic programming for the optimal bidding in iterative auctions.
- Forth, related to the previous point, the risk management within the BGP and WDP models still needs attention from the scientific community (see Spadoni & Potters, 2018).
- Finally, many procurement managers prefer to adopt simple RCA designs in order to avoid applicability complications, even though at the price, sometimes, of losing part of the auction efficiency and economic benefits. However, it would be interesting to explore, for each application, several RCAs designs including the multi-round auction mechanism and/or the potentialities that the different features of the bidding languages can offer.

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