EVOLUTIONARY ALGORITHMS IN AUCTION MODELS OF SERVICE PROCUREMENT

by

LEE CHEN WEI

Thesis submitted in fulfilment of the requirements for the degree of Master of Science

April 2019

ACKNOWLEDGEMENT

I would like to thanks my supervisors, associate professor Dr Joshua Ignatius, associate professor Dr Wong Wai Peng and Dr Amirah Rahman for leading me throughout this research. I have exposed to a lot of new ideas in this field under their guidance and advices. Not to mention my appreciation to Dr Tan Choo Jun that helps me in coding.

Besides that, I also want to thanks to my family as they always give me support mentally. It helps me to overcome negative emotions. It would be very tough without their support.

Lastly, I would thanks to my friends for sharing their knowledge and ideas with me. We had exchanged our ideas to have a better understanding in this field.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

LIST OF ABBREVIATIONS

B2B	Business to Business
C2C	Consumer to Consumer
CA	Combinatorial Auction
CDA	Combinatorial Double Auction
DA	Double Auction
GA	Genetic Algorithm
IoT	Internet of Things
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Problem
MOEA	Multi-Objectives Evolutionary Algorithm
NFE	Number of Fitness Evaluation
NSGA-II	Non-dominated Sorting Genetic Algorithm
NSGA-III	Reference-point based Non-dominated Sorting Genetic Algorithm
PAES	Pareto Archived Evolution Strategy
SPEA2	Strength Pareto Evolutionary Algorithm
WDP	Winner Determination Problem

ALGORITMA EVOLUSI DALAM MODEL LELONGAN PEROLEHAN PERKHIDMATAN

ABSTRAK

Dalam masalah penentuan pemenang (WDP) berasaskan lelongan kombinatorial (CA) untuk bidang perolehan perkhidmatan pengangkutan, pembekal perkhidmatan penghantaran menawarkan pakej-pakej berdasarkan laluan yang diminta oleh peminta penghantaran. Dengan perkembangan teknologi dan internet, perkhidmatan yang memerlukan keputusan dalam jangka masa yang pendek seperti penghantaran sambungan terakhir semakin mendapat perhatian. Walau bagaimanapun, para penyelidik sebelum ini memberi tumpuan kepada penyelesaian model integer campuran untuk WDP berasaskan CA. Cara tersebut tidak cekap untuk senario berskala besar. Oleh itu, kami mencadangkan pelaksanaan algoritma genetik (GA) bersama dengan pengendali berasaskan pengetahuan sebagai alternatif untuk mendapatkan penyelesaian anggaran. Perbandingan antara hasil dari model dan algoritma yang berbeza termasuk model linear berasaskan CA yang diselesaikan oleh pengaturcaraan linear integer campuran (MILP), model bukan linear berasaskan CA yang diselesaikan oleh konvensional GA dan model terurai yang diselesaikan oleh GA yang dicadangkan. Dalam senario berskala besar, GA yang dicadangkan boleh mendapatkan kos yang lebih rendah berbanding dengan MILP dalam jumlah masa yang sama. Di samping itu, GA yang dicadangkan juga mempunyai fleksibiliti yang lebih baik untuk pasaran penjelasan. Selepas itu, kami melaksanakan algoritma evolusi multi-objektif (MOEAs) dengan konsep yang sama dalam GA yang dicadangkan kepada bi-objektif WDP berasaskan lelongan berganda kombinatorial (CDA). MOEAs yang digunakan dalam penyelidikan ini termasuk algoritma genetik mengikut susunan tidak didominasi II (NSGA-II), algoritma genetik mengikut susunan tidak didominasi

III (NSGA-III), strategi evolusi pareto yang diarkibkan (PAES) dan algoritma evolusi kekuatan pareto (SPEA2). Secara umumnya, NSGA-II, NSGA-III dan SPEA2 boleh mendapatkan penyelesaian anggaran dalam masa pendek walaupun ketepatan akan berkurang secara sedikit dalam senario berskala besar.

EVOLUTIONARY ALGORITHMS IN AUCTION MODELS OF SERVICE PROCUREMENT

ABSTRACT

In combinatorial auction (CA) based winner determination problem (WDP) for transportation service procurement, carriers bid in packages according to lanes advertised by shipper. Along development of technologies and internet, last mile delivery, a service that needs fast decision is getting attention. However, previous researchers focused on solving mixed integer model for the CA based WDP, which is not efficient for large scale instance. Therefore, this research proposed an implementation of genetic algorithm (GA) with knowledge based operators as an alternative to approximate the solution. The comparison of the results includes linear CA based model solved by mixed integer linear programming (MILP), non-linear CA based model solved by conventional GA and decomposed model solved by proposed GA. The results show that the proposed GA can obtain lower cost using the same amount of time compared to MILP in large scale instance. Furthermore, the proposed GA also has better flexibility for market clearing. After that, using same concept in proposed GA, multi-objectives evolutionary algorithms (MOEAs) are implemented to bi-objectives combinatorial double auction (CDA) based WDP. The MOEAs that were implemented in this research includes Non-Dominated Sorting Genetic Algorithm II (NSGA-II), Non-Dominated Sorting Genetic Algorithm III (NSGA-III), Pareto Archived Evolution Strategy (PAES) and Strength Pareto Evolutionary Algorithm (SPEA2). Generally, the results show that NSGA-II, NSGA-III and SPEA2 are able to get the approximation set of solutions quickly although their accuracies tend to be slightly reduced for large scale case.

Chapter 1 - Introduction

1.1 Auction

Auction is the process that buys or sells goods or services by bidding. It is a mechanism that is reliable in business transactions. In an ordinary auction (forward auction), buyers compete with each other by bidding higher price to get the goods or services sold. However, it usually happens to be reversed in procurement services where seller underbid each other to get their business sold. This type of auction is called reverse auction. Reverse auction is an innovative market mechanism to reduce the cost of purchased goods and services for e-business or so called e-commerce, business that is conducted using internet (Emiliani, 2000) even though e-business has dynamic, rapidly growing and highly competitive characteristic (Amit and Zott, 2001). Reverse auction mechanism is applied in different fields, such as resource allocation problem (Wang et al., 2013), procurement problem (Thurston et al., 2010), transportation service procurement problem (Foster and Strasser, 1990) and so on.

In transportation service procurement, request for proposal is a traditional process that usually bids for contract that lasts for one or two years (Foster and Strasser, 1990). Its process includes estimating the demand by using the information from past years, then offers lanes for carriers (seller) to bid. The 'lanes' is subjected to origins and destinations that shipper (buyer) wants his load to be carried.

In general, the outlines of auction system in transportation service procurement are:

1. Shipper opens lanes for carriers to bid
2. Carriers bid on available lanes
3. Winner determination algorithm is done to determine winner.

However, if each lane is evaluated in an individual reverse auction independently, in economic aspect, it makes sense for shipper but it is not for carriers. Carriers need to account for the utilization of their equipment and balance the need for the equipment and drivers (Sheffi, 2004). This increase the bid price of the carriers to cover the risk of empty load and indirectly increase shipper's cost to buy the service as well. In fact, Sears Logistics Services used combined-value auction and were successful to reduce this hidden cost and saved 13% over past procurement practices (Ledyard et al., 2002). However, combined-value auction is rarely being used, perhaps lacking knowledge and experience. Later, Caplice and Sheffi (2003) found that optimization-based method should be applied to transportation service procurement due to strong presence of economies scope. Therefore, Sheffi (2004) solved transportation procurement problem considering carriers' economic scope by formal optimization method including the level of services of carriers.

1.2 Literature of Auction based Winner Determination Problem in Transportation Service Procurement

Considering the issue of carriers' economic aspect, combinatorial auction (CA) is introduced as an auction mechanism to facilitate bidding for lanes by carriers in packages (Caplice and Sheffi, 2003; Ledyard et al., 2002). In other words, it is an "all or nothing" mechanism such that if carrier fails to attain one of the lanes in the package bid, he does not need to fulfill the other lanes within the package. Following this, carriers could confidently bid their true values given that hidden cost is reduced; hence ultimately benefiting the shipper. CA is a very popular method in transportation service procurement problem as carriers want to maximize their utility. In fact, Song and Regan (2003) had studied to use CA based on carriers' perspective and found that both shipper and carriers are able to gain significant benefits. Figure 1.1 shows an example of a reverse CA. Let A, B, C and D be the transportation service in transportation service procurement. If shipper wants to buy transportation services A and B at the same time, instead of buying the services from 2^{nd} and 8^{th} bids, the 1^{st} packages bids are cheaper. Therefore, the carrier that offered 1^{st} packages bid will get the business.

Items / services to be bided:
{A, B, C, D}

Price offered:

\$6	**\$4**	**\$5**	**\$4**	**\$5**	**\$7**	**\$4**	**\$3**	**\$2**
A	B	C	C	B	A	A	A	D
B		D		D	B	D		
					D			

Figure 1.1. Example of CA

CA based winner determination problem (WDP) in transportation service procurement is complex (Rekik and Mellouli, 2012; Chen, 2016; Sandholm, 2002) and the complexity would be increased if decision makers have to account more properties in their WDP. For example, one of the properties that decision makers might account is the flexibility of their WDP. Ignatius et al. (2010) leverage on the imprecision of bid prices as a means to provide flexibility to the WDP. Besides that, to counter the issues of uncertainties of price, Ignatius et al. (2011) formalized a Fuzzy Combinatorial Auction Winner Determination Problem (Fuzzy CA WDP) that allows the auctioneer to estimate its "true" revenue despite price uncertainties. Then Ignatius et al. (2014) were the first to consider multi-objective properties for the winner determination CA mechanism and provide solution comparisons across weighted objective method, preemptive goal programming, and compromise programming.

Different methods were proposed in dealing with complex CA based WDP. For example, Wu et al. (2015) recast the WDP into maximum weight clique problem

(MWCP) and used multi-neighborhood tabu search. Ma et al. (2010) proposed a 2-stage stochastic integer programming for WDP to hedge the shipper's risk under shipment uncertainty. Not to mention Remli and Rekik (2013) proposed a constraint generation algorithm to solve a robust WDP for combinatorial transportation auctions.

Other than CA mechanism, another auction mechanism that is commonly used in transportation service procurement is double auction (DA). It is an auction which considers a multi-seller and multi-buyer environment. In this environment, a third party act as auctioneer, collecting the bids from sellers and buyers. The auctioneer could also be an independent platform or cloud-based electronic transportation market. In such a situation, the electronic transportation market will regulate the price that allow clearance or matching between bids. Similar with CA, DA is able to reduce hidden cost and achieving satisfaction for sellers and buyers too. The idea is to match up 'suitable' sellers and buyers to minimize the cost. Therefore, this mechanism is efficient in thick market. One of the studies on DA is to implement a dynamic environment for single-lane transportation problem (Xu and Huang, 2013). Recently, Ling et al. (2016) examined bidding strategies and their impact on the transportation services market. The DA mechanism has also been extended for a multi-attribute setting by Cheng et al. (2016) in the context of perishable supply chain trading.

Combinatorial double auction (CDA) has both DA and CA properties. It considers a multi-seller and multi-buyer environment while allowing the participants to bid on multiple lanes in a package. CDA has just been applied to transportation service procurement recently. Similar to DA, the auctioneer can be a third party agent or an electronic transportation market. To date, there is very little documented research on CDA in transportation service procurement. Motlagh et al. (2010) derived a linear CDA model in transportation service procurement that allows carriers to constraint the range of load volume to be carried. The derived CDA model is compared with CA using test procedure. The results show that CDA is superior to CA by generating more revenue, and it remains relatively stable for reduced market clearing flexibility. CDA is also used in business-to-business (B2B) trading in a centralized marketplace, or in a multi-agent coordination system with artificial intelligence. Xia et al. (2005) showed how a general CDA problem could be reduced to a combinatorial single-sided auction. Other applications of CDA include native vegetation offsets shown in Nemes et al. (2008), a trust incentive problem shown in Wang et al., (2010), and cloud computing in Samimi et al. (2014). Figure 1.2 shows the simple relations to differentiate normal auction, CA, DA and CDA.

	One Seller Many Buyer	*Many Seller Many Buyer*
Package Bid	**Combinatorial Auction**	**Combinatorial Double Auction**
Non-package Bid (Simple Bids)	**Normal Auction**	**Double Auction**

Figure 1.2. Types of auction mechanisms

Along with internet and technologies development, one of the transportation services, last mile delivery is becoming important in logistic companies. This is because of the increasing amount of transactions in e-commerce (Leonard, 2012; McLaughlin et al., 2017). However, Ducret (2014) investigated parcel deliveries and urban logistics in French. It is found that last mile delivery is still understudied, which is generally more expensive, less efficient and the most polluting sections in logistic chain (Gevaers et al., 2014). The main problems of last mile delivery include uncertainty in terms of traffic that will influence the delivery process and the substantial pollution emissions (Tavana et al., 2017). Therefore, Tavana et al. (2017) suggested that using unmanned aerial vehicle, which commonly known as drone, can reduce the influence of the aforementioned issues and therefore, the service provided can be faster and more reliable.

1.3 Literature of Drone Delivery

Technological advancement has made drone delivery a reality, which is able to change the common choice of delivery options as drone can be operated autonomously and unconstrained by road traffic conditions (Dorling et al., 2017; Marius Johansen, 2017). Besides that, Goodchild and Toy (2017) estimated the emission of carbon dioxide and vehicle miles travelled levels. They found that using drone, rather than truck, can reduce carbon dioxide emissions if the service zones are close to depot or the carried load is light in weight.

To resolve the routing problems in drone deliveries, different methods have been examined. Sundar and Rathinam (2014) optimized the routing problem of single drone with multiple depots and multiple targets where the depots allow drone to refuel. Guerriero et al. (2014) presented a multi-objectives mathematical formulation. It treats the drone routing system as dynamic scheduling problem. Murray and Chu (2015) modelled a flying sidekick traveling salesman problem to optimize the routing and schedule of trucks and drones' collaboration. Ferrandez et al. (2016) showed another way of trucks and drones collaboration. It aims to optimize the delivery network. Dorling et al. (2017) considered the issues of battery weight, payload weight and drone reuse in their vehicle routing problem.

From the previous literatures, it can be concluded that with the current technologies, drone delivery still has limitation, but has some advantages over truck delivery in certain scenarios. However, the marketplace of e-commerce is a significant area for drone delivery to work well. This is because there are a lot of transactions in e-commerce that the goods are light in weights (Wang, 2016). Unlike drone routing problems presented in the literatures, this research proposes to use the WDP method to assign an optimised pair between customers and logistic companies within a pool of data supplied by customers and logistic companies. By having large enough pool of customers and logistic companies, despite whether drone delivery is used in tandem with trucks, the routing problem optimized by the logistic companies is more practical in the economic sense. The current literature mainly focused on routing from the technical aspect, while the economic aspect of drone delivery is yet to be fully explored. As the use of drone in last mile delivery is increasingly gaining importance in today's e-commerce era, the need to look at drone transport service procurement is timely and vital. In this regards, transport service procurement is actually a WDP issue.

Despite the auction mechanism implemented, the WDP mentioned is expected to be in big demand and participated by huge number of customers. Besides that, auctioneers need a method that will quickly yield a solution for on demand delivery services. However, from the combinatorial transportation auctions presented by Ma et al. (2010) and Remli and Rekik (2013), mixed integer linear programming (MILP) generally needs very long time to compute the solution when the number of lanes and number of package bids are large. Therefore, an alternative solution for this issue is to use metaheuristic methods. The common heuristic methods used are simply greedy heuristics, simulated annealing and genetic algorithm (GA). This research uses GA as solution as it is one of the most popular heuristic method and versatile in most of the problems. Further, those three heuristic methods mentioned are compared in Schwind et al. (2003) to optimize the resource allocation problem and GA outperform others.

1.4 Literature of Genetic Algorithm

GA is a heuristic method that undergoes a probability search algorithm to find a solution based on natural genetic evolution of a population. It is a popular algorithm that is widely used, for example in channel assignment problem (Fu et al., 2006), multiproduct multistage production system (Korytkowski, 2011) and two-echelon capacitated vehicle routing problem (Wang et al., 2017). The general reviews of GA and its application could be found in Kumar et al. (2010). GA has also been used to solve CA mechanism in other fields such as dynamic and complex task allocation problem in multi-robot cooperation (Gong et al., 2007) and procurement process (Patodi et al., 2011). The results of these studies show that GA can handle CA mechanism well.

Efficiency is one of the main concerns in implementing heuristic methods. Although applying conventional GA to the non-linear CA based WDP model is simpler for auctioneers, the efficiency of the conventional GA needs to be revised. Regarding the efficiency of heuristic methods, many studies have investigated ways to improve different models and problems. In a supply chain scheduling problem, Pei et al. (2016) derived a two-phase heuristic (TP-H) procedure which is superior to modified first fit (MFF) and modified best fit (MBF). In the paper reel layout problem, where transportation cost is minimized by determining the layout when assigning paper reel types into cell space, Lai et al. (2002) decompose the model for ease of interactive solution by the simulated annealing method. Wang et al. (2014) presented a biogeography-based krill herd (BBKH) algorithm to improve the performance of krill herd (KH) in solving complex optimization task. Focusing more on GA, Lopes et al. (2016) proposed a hybrid GA for the capacitated location-routing problem. The proposed chromosome representation and crossover operator and search procedures are relatively simple but effective, providing competitive results within a reasonable time. Similarly, Dao et al. (2016) also proposed an effective GA to solve a large-scale traveling salesman problem. They proposed generating procedures for obtaining the initial population that considers the locations of cities, and crossover and mutation functions that are more suitable to solve the large-scale traveling salesman problem. Dou et al. (2016) proposed a multi-stage interactive GA for product customization. Further, some researchers imply knowledge based techniques to the operators of GA to initialize and evolve the population more efficiently (Hu and Yang, 2004; Li et al., 2016).

There are cases that electronic transportation market needs to consider more than one objective. Therefore, some reviews on few Multi-Objectives Evolutionary Algorithms (MOEAs) that developed based on GA framework are shown in next subchapter.

1.5 Literature of Multi-Objectives Evolutionary Algorithms

Normally, the WDP model needs to consider more than one objectives, which often are in contradiction in most real cases, as considered in this research. In such situation, it is not possible to get a solution that minimizes or maximizes both objectives. Decision makers need to search for a set of trade-off optimal solutions, known as the non-dominated Pareto-optimal solutions (Deb, 2001). To solve multi-objectives problems, the classical weighted objectives method can be considered (Geoffrion, 1968). However, the solutions set can only be obtained through multiple runs with different objectives weights, which is a time-consuming and laborious process. Population-based multi-objectives algorithms, for example MOEAs, are able to produce a set of Pareto optimal solutions in single run. Therefore, MOEAs are popular and has been widely accepted as a useful method for solving multi-objectives problems

(Zhou et al., 2011). Furthermore, to solve large instances in the complex WDP models, metaheuristic methods, which include MOEAs, constitute a practical approach.

MOEAs are mostly developed from single objective evolutionary algorithm. Examples include the Multi-Objective Genetic Algorithm (Fonseca and Fleming, 1993), Non-dominated Sorting Genetic Algorithm (Srinivas and Deb, 1994), and Niched Pareto Genetic Algorithm (Horn et al., 1994). In general, the two common features of MOEA operators are assigning a fitness to each population member based on a non-dominated sorting procedure and preserving diversity among the solutions of the same non-dominated front. To produce better solutions, the elitism strategy is adopted (Zitzler et al., 2000). Some elitist MOEA examples include Strength Pareto Evolutionary Algorithm (Zitzler and Thiele, 1998), Pareto-archived Evolution Strategy (Knowles and Corne, 1999) and elitist GA (Rudolph, 2001).

Besides that, another aspect is hybridizing the algorithm by combining local search algorithm to multi-objective genetic operations which is called memetic algorithm (Ishibuchi and Murata, 1996). Mashwani et al. (2017) further developed hybrid NSGA which includes adaptive operator selection recently. There are also researchers that study on MOEA based on decomposition, MOEA/D where the multi-objectives problem is decomposed to sub problems to be optimized simultaneously (Zhang and Li, 2007). For dynamic cases, Jiang and Yang (2017) developed a steady-state and generational evolutionary algorithm. Some examples of applications of MOEAs include data mining (Mukhopadhyay et al., 2014a; Mukhopadhyay et al., 2014b), spectrum assignment problem (Martínez-Vargas et al., 2016) and power flow problem (Zhang et al., 2016). A comprehensive survey of some popular MOEAs technique in solving multi-objectives problems is presented by Coello (1999). Coello (1999) introduced the strength and weakness of those MOEAs that were popular before year

2000. Zhou et al. (2011) also carried out a survey on MOEAs and presented the state of the art of MOEAs.

In this research, four widely used MOEAs will be employed to tackle the CDA based WDP model for last mile drone delivery. They are Non-dominated Sorting Genetic Algorithm (NSGA-II), reference-point based Non-dominated Sorting Genetic Algorithm (NSGA-III), Pareto Archived Evolution Strategy (PAES) and Strength Pareto Evolutionary Algorithm (SPEA2). A review on these MOEAs and their associated characteristic features are described as follows.

NSGA-II uses a fast non-dominated sorting procedure for ranking the solutions in its selection and crowding distance assignment (Deb et al., 2002). In NSGA-II, for each solution, two entities are calculated:

- Domination count (the number of solutions which dominate the solution)
- A set of solutions that a particular solution dominates

The solution that has zero domination count occupies the first front. The domination count is reduced accordingly for the subsequent fronts. Based on this NSGA-II framework, Deb and Jain (2014) suggested a reference point based many objectives evolutionary algorithm, namely NSGA-III. Jain and Deb (2014) further extended NSGA-III for solving generic constrained problems. The basic framework of NSGA-III is similar to that of NSGA-II, but with significant changes in its selection operator (Deb and Jain, 2014; Jain and Deb, 2014). The crowding distance operator is replaced with methods that maintain diversity among the population members by supplying and adaptively updating a number of well-spread reference points.

On the other hand, PAES uses its pareto archive for evolution with a local search. The local search starts from a population of one, based on a reference archive from the previous solutions (Knowles and Corne, 1999). In PAES, after the evaluation of one chromosome (current solution), a copy of that chromosome is mutated to form new candidate solutions. The current and new candidate solutions are compared. If one solution dominates the other, the non-dominated solution is absorbed into the archive. For neither solution dominates one another, the candidate solution is compared with a reference population of previously achieved non-dominated solutions. If the comparison fails to favour one candidate solution over the existing ones, the solution which resides in the least crowded region of space is selected.

Lastly, SPEA2 uses a fine-grained fitness assignment strategy, a density estimation technique, and an enhanced archive truncation method (Zitzler et al., 2001) in its algorithm. In the fitness assignment state of SPEA2, a strength value is assigned to each member in the population and the archive (an external set) according to the number of solutions it dominates (Zitzler et al., 2001). The raw fitness value is calculated according to the strength value. The density estimation technique used is an adaption of the k-th nearest neighbour method (Silverman, 1986). The fitness value is calculated by adding both the raw fitness value and the density estimation value. Differ to SPEA, SPEA2 has a fixed number of individuals in its archive. Therefore, the dominated individual may be copied to the archive if the number of non-dominated individuals is smaller than the fixed number of individuals in the archive.

The aforementioned MOEAs are widely applied in different fields. Examples include an inventory control system (Cholodowicz and Orlowski, 2017) and an operational planning problem (Alexandre et al., 2017). In both applications, NSGA-II and SPEA2 were used and compared. On the other hand, in a partial flexible job shop scheduling problem (Rabiee et al., 2012), NSGA-II and PAES were used. In general, these MOEAs outperform each other in different fields.

1.6 Problem Statement

In transportation service procurement, CA is a common mechanism used to form WDP that determine which carriers' bid win the business. Although CDA based WDP in transportation service procurement had shown its potential in terms of market clearing flexibility (Motlagh et al., 2010), its literature is still scarce. Besides, researches up to date mostly developed mixed integer model solved with MILP for both CA and CDA based WDP. This might face inefficiency when solving the complex WDP; such as, WDP that need to solve large number of lanes and package bids, WDP that has tight constraint and WDP that implied multi-objectives properties. Inefficiency mentioned is mainly referring to how long the decision maker can get the solution. This is because along the development of digital business, WDP in transportation service procurement needs to be solved very quickly.

1.7 Research Objectives

The main objective of this research is to imply metaheuristic method to the CA and CDA based WDP in transportation service procurement so that the complex WDP can be solved quickly. Besides that, this research also aims to develop a metaheuristic algorithm and model that are able to get the approximated solution more efficiently including scenarios that make the model complex. Last but not least, this research wants to imply bi-objective to CDA based WDP model in this field and then compare the results solved by some popular MOEAs.

1.8 Contributions of the Research

In this research, the main contribution is the analysis of the needs to implement metaheuristic methods to CA and CDA based WDP in transportation service procurement. Firstly, a non-linear CA model is derived to be solved with conventional GA (built-in GA function from analytical software). Secondly, this research also decomposes the MILP model to 2-stages and then propose an implementation of GA with knowledge based operators. Thirdly, the results of the models derived is compared with linear CA model solved with MILP on their accuracy, duration and flexibility. Fourthly, considering last mile delivery with drone, CDA based bi-objectives WDP model which is unprecedented is proposed. Lastly, MOEAs are applied to find the solutions for the WDP model to handle large and complex scenarios. The convincing solutions indicate that metaheuristic methods are able to provide solutions for large and complex scenarios, therefore overcoming the inefficiency issue associated with large and complex WDP models in the marketplace.

1.9 Organization of Thesis

Chapter 2 will analyze different types of CA based WDP that are to be solved using different methods. Then, chapter 3 implement bi-objective to CDA based WDP and solve it using some popular MOEAs. Chapter 4 is the discussion and managerial implications of these models. Lastly, chapter 5 concludes the research.

Chapter 2 - Winner Determination Problem in Transportation Service Procurement with Cost and Market Clearing Flexibility

We are entering an era where digital and physical worlds begin to blur (Scheibenreif, 2014). Following the rapid growth of Internet of Things (IoT) and cloud computing where most data are exchanged and processed in the internet, the number of digital businesses or business moments are rapidly increasing as well. One of the branches of digital business is consumer to consumer (C2C) services provided through e-commerce. The transaction in C2C services is rapidly increasing (Leonard, 2012; McLaughlin et al., 2017). E-commerce such as Big Commerce can also be a platform that hosts independent online stores in one online location. In such a platform, delivery services can be treated as one of the IoT resources and auctions could take place in this marketplace (Lopez, 2012; Safianowska et al., 2016). These business moments make some logistic companies realize the opportunity in last mile delivery. For example, DHL executed on demand delivery that was developed in response to significant growth in cross-border e-commerce volumes (Ian, 2016).

In this chapter, the combinatorial auction (CA) based winner determination problem (WDP) for delivery or shipment process considered is in such an e-commerce platform. A big challenge for the delivery system in this platform is that auctioneers need to assign respective carriers to deliver goods over a short period of time. In other words, the CA based WDP has to be solved in a short amount of time. However, most of the algorithms developed currently are only able to solve small and moderate scale CA based WDP quickly in transportation service procurement (Ma et al., 2010; Remli and Rekik, 2013). This is because traditional transportation services are mostly bid through request for proposal that provides services for years. Therefore, researchers tend to seek an optimal solution using mixed integer linear programming (MILP) than approximating solution by heuristic methods. To solve a large scale scenario in short time, there is a need to use heuristic methods to find an approximated solution. As a step toward metaheuristic methods, genetic algorithm (GA) will be used to solve the CA based WDP analyzed in this chapter. GA is chosen because of its popularity and flexibility in the sense that it is able to yield a good approximated solution in most problems (Kumar et al., 2010).

The simplest way to implement GA is to plug in linear CA based WDP model in the default setting of the GA function in some analytic software such as Matlab R2014a. Note that most of the commercial software for optimizations provide a built-in GA function. Therefore, this built-in GA function is defined as conventional GA throughout this research. However, by simply plugging in the model to conventional GA usually offer no solution. This is because the covered search space of the linear model has too many infeasible solutions while the default operators of GA are not specified to search for those relatively few feasible solutions out of the search space. To counter this issue, two solution methods will be analyzed: non-linearize the model to enable conventional GA get approximated solution, and decompose the model to be solved using proposed GA. In proposed GA, knowledge based operators will be implemented. Therefore, in general, four different types of models using different solution methods for the WDP are considered:

- Conventional reverse auction that simultaneously runs multiple units of independent auctions on each lane solved by MILP.
- Linear CA based WDP model solved by MILP.
- Non-linear CA based WDP model solved by conventional GA
- Decomposed CA based WDP model solved by proposed GA.

Notice that a lane is defined as a path that represents the loads that will be shipped from an origin to a destination. In each model, carriers are able to submit a lower bound and an upper bound for each lane (whether it is package bid or not) to ensure the assigned carriers to have at least the profit of the lower bound submitted in their bid. This can encourage more carriers to participate in the auction (Ma et al., 2010; Motlagh et al., 2010).

2.1 Mathematical Models

2.1.1 Indices, Parameters and Decision Variables

In this subchapter, the indices, parameters and decision variables of the four models are introduced.

Indices:

I : Set of shipping origin

J : Set of shipping destination

N : Set of carriers

C : Set of carriers' bidding packages

Parameters:

a_{ij} : Demand of shipper in lane *i* to *j*

B_{ij}^{n} : Total supply of carrier in lane *i* to *j*

b_{ij}^{c} : Supply of package c from carriers in lane *i* to *j*

p_{ij}^{c} : The price per unit volume in lane *i* to *j* of package *c*

L_{ij}^{c} : The minimum volume of load that is acceptable in lane *i* to *j* in package *c*

U_{ij}^{c} : The maximum volume of load that is acceptable in lane *i* to *j* in package *c*

Decision Variables:

x_{ij}^{c} : Proportion of load accepted for package c on lane i to j

y^{c} : Decide whether or not to accept package c

where $i \in I, j \in J$ $c \in C$ and $n \in N$. In the following subchapters, lane (i, j) means the lane where the origin is i and destination is j.

2.1.2 Reverse Auction Model

In transportation service procurement, when more than one lane is open for bidding, a simultaneous multiple unit auctions could be formed. This is a reverse auction model as each lane is treated as an individual reverse auction. The objective function is to minimize the cost for each lane. Referring to the general model developed in Motlagh et al. (2010), carriers could submit bids for every lane in a range for every package. The reverse auction model formed is shown in equation (2.1) to (2.6).

$$\text{Min} \sum_{c \in C} \left(p_{ij}^{c} b_{ij}^{c} x_{ij}^{c}\right) \tag{2.1}$$

s.t

$$-\sum_{c \in C} b_{ij}^{c} x_{ij}^{c} \leq -a_{ij} \tag{2.2}$$

$$-b_{ij}^{c} x_{ij}^{c} + L_{ij}^{c} y^{c} \leq 0 \qquad \forall\, c \tag{2.3}$$

$$b_{ij}^{c} x_{ij}^{c} - U_{ij}^{c} y^{c} \leq 0 \qquad \forall\, c \tag{2.4}$$

$$x_{ij}^{c} \in \mathbb{R}^{+} \qquad \forall\, c \tag{2.5}$$

$$y^{c} \in \{0,1\} \qquad \forall\, c. \tag{2.6}$$

Equation (2.1) is the objective function that minimizes the cost for lane i to j. The total cost can be found by adding up the objective function values of every auctioned unit. Equation (2.2) ensures the supply from carriers is greater than demand for a particular lane. The acceptable volume of load of carriers for lane i to j is constrained by equation (2.3) and (2.4). Notice that when $y^c = 1$,

$$\frac{L_{ij}^c}{b_{ij}^c} \leq x_{ij}^c \leq \frac{U_{ij}^c}{b_{ij}^c}$$

or when $y^c = 0$,

$$x_{ij}^c = 0.$$

2.1.3 Linear Combinatorial Auction Model

If the bids could be submitted in packages, such as bundling of lanes in the context of transportation service procurement problem, one could form a CA model. All bids for lanes submitted are given equal importance in this form of auction and this makes the model more complex (Motlagh et al., 2010). Equations (2.7) to (2.12) show the CA model for the transportation service procurement problem.

$$\text{Min} \sum_{c \in C} \sum_{(i,j) \in (I,J)} p_{ij}^c b_{ij}^c x_{ij}^c \tag{2.7}$$

s.t.

$$-\sum_{c \in C} b_{ij}^c x_{ij}^c \leq -a_{ij} \qquad \forall\ (i,j) \tag{2.8}$$

$$-b_{ij}^c x_{ij}^c + L_{ij}^c y^c \leq 0 \qquad \forall\ c,(i,j) \tag{2.9}$$

$$b_{ij}^c x_{ij}^c - U_{ij}^c y^c \leq 0 \qquad \forall\ c,(i,j) \tag{2.10}$$

$$x_{ij}^c \in \mathbb{R}^+ \qquad \forall\ c,(i,j) \tag{2.11}$$

$$y^c \in \{0,1\} \qquad \forall\ c. \tag{2.12}$$

Equation (2.7) is the objective function to minimize total cost while equation (2.8) ensures the supply of carriers is greater than demand for all lanes. The acceptable volume of load carried by carriers for all lanes is constrained by equations (2.9) and

(2.10). Notice that each of the carriers might have different number of packages. Minimizing shipper's cost means minimizing the sum of the prices for all assigned packages. For example, if there are 3 carriers, each of them summited 2, 4 and 3 packages respectively, there will be 9 packages in total as shown in Table 2.1.

Table 2.1
Example of encoded c

Carrier n	Number of packages	Package c
1	2	$c = \{1,2\}$
2	4	$c = \{3,4,5,6\}$
3	3	$c = \{7,8,9\}$

The cost of package c is

$$\sum_{(i,j)\in(I,J)} (p_{ij}^c \times b_{ij}^c \times x_{ij}^c)$$

and the sum of all the cost of packages is the total cost. Similarly, $y^c = 1$ means package c is assigned and otherwise.

The CA model shown in equations (2.7) to (2.12) is a mixed integer problem (MIP) that could be solved using MILP method. However, it is impractical to solve the model using MILP techniques in real situations that are in large scale as it may result in a lengthy execution time. Ma et al. (2010) show a similar two-stage stochastic integer programming model that can solve moderate scale instances of stochastic WDP in reasonable time using commercial solvers. However, their model did not allow to set different load volumes for each lane in the respective packages which is restrictive to auctioneers. Not to mention it is still costly in terms of time to solve large scale instances.

2.1.4 Non-Linear Combinatorial Auction Model

Besides the model proposed in Ma et al. (2010) that only able to solve moderate scale instances in reasonable time, another similar model from Remli and Rekik (2013) failed to get solution within time limit of 10 hours in some large scale instances. Therefore, considering large scale WDP, GA is applied to approximate the solution of the model. However, using conventional GA (built-in GA function in MatlabR2014a) in the linear model shown in equations (2.7) to (2.12) yields no solutions. This is because the limit

$$\frac{L_{ij}^c}{b_{ij}^c} \leq x_{ij}^c \leq \frac{U_{ij}^c}{b_{ij}^c},$$

when $y^c = 1$, or

$$x_{ij}^c = 0,$$

when $y^c = 0$,

constrains the search space of the domain in GA by including too many infeasible elements, while default operators in conventional GA do not specify to find the feasible solutions out of the covered space like MILP does. Therefore, to counter this issue, non-linearize CA model is introduced, as in equations (2.13) to (2.16).

$$\text{Min} \sum_{c \in C} \sum_{(i,j) \in (I,J)} p_{ij}^c b_{ij}^c x_{ij}^c y^c \tag{2.13}$$

s.t.

$$a_{ij} - \sum_{c \in C} b_{ij}^c x_{ij}^c y^c \leq 0 \qquad \forall\, (i,j) \tag{2.14}$$

$$x_{ij}^c \in \left(L_{ij}^c / b_{ij}^c, U_{ij}^c / b_{ij}^c\right) \qquad \forall\, c, (i,j) \tag{2.15}$$

$$y^c \in \{0,1\} \qquad \forall\, c \tag{2.16}$$

Equation (2.13) is the non-linear objective function to minimize the cost and equation (2.14) ensure supply is greater than demand. Notice that equation (2.15) constraint the search space of x_{ij}^{c} to the range submitted by carriers. This greatly reduces the infeasible elements in the searching space of the domain in GA.

2.1.5 Decomposed Combinatorial Auction Model

Although approximating CA model with conventional GA method is "user-friendly", it is predicted to be less efficient. Therefore, in reconsidering the MIP, there are two levels of variables. The first level of binary variables determines whether the package is assigned, whereas the second level variables determines the assigned proportion of loads in each lane of the assigned packages. The second level variables are dependent on the first level variables as the proportion of loads is meaningless if the respective packages are not assigned. Therefore, to reduce redundant iterations in GA, MIP is decomposed into two stages. The idea is to determine the assigned packages, subsequently optimize the proportion of loads for each lane in the assigned packages. It can be summarized as:

1. Assigning the packages (values of $\tilde{y}$)
2. Find the optimal proportion of loads for the assigned packages (values of $\tilde{x}$)

Decomposed model:

$$\text{Min } F(\tilde{y}, \tilde{x}) \qquad (2.17)$$

s.t.

$$-\sum_{c \in C} \left(UB_{ij}^{c} y^{c}\right) \leq -a_{ij} \qquad \forall\ (i,j) \qquad (2.18)$$

$$y^{c} \in \{0,1\} \qquad \forall\ c \qquad (2.19)$$

$F(\tilde{y},\tilde{x})$ in equation (2.17) is the fitness function to find the fitness value of $\tilde{y}$. Equation (2.18) ensures supply is greater than demand; that is, it ensures $\tilde{y}$ is feasible. To score $\tilde{y}$ (determine the fitness value $\tilde{y}$) in the scoring phase, the model shown in equations (2.20) to (2.22) is solved.

$$F(\tilde{y},\tilde{x}) = \text{Min} \sum_{k\in(C\,\cap\,y^k=1)} \sum_{(i,j)\in(I,J)} \left(p_{ij}^k b_{ij}^k x_{ij}^k\right) \tag{2.20}$$

s.t.

$$-\sum_{k\in(C\,\cap\,y^k=1)} \left(b_{ij}^k x_{ij}^k\right) \leq -a_{ij} \qquad \forall\,(i,j) \tag{2.21}$$

$$x_{ij}^k \in \left[LB_{ij}^k/b_{ij}^k, UB_{ij}^k/b_{ij}^k\right] \qquad \forall\, k,(i,j) \tag{2.22}$$

Note that $k \in C$ and $y^k = 1$, indicating only proportion of loads for assigned packages are considered in the model. Equation (2.20) minimizes the cost of the shipper while equation (2.21) ensures the supply demand constraint is fulfilled. For a clearer picture, assuming that there are 3 packages submitted such that each of them has 2 lanes at location 1 and 2, if $\tilde{y} = \{1,0,1\}$, the proportion of loads to be solved are $\tilde{x} = \{x_{12}^1, x_{21}^1, x_{12}^3, x_{21}^3\}$. Notice that this is a linear model and could be easily solved using linear programming (LP).

2.2 NP-hardness

The NP-hardness of the model could be derived by transferring an arbitrary instance of the bin-packing problem into an instance of the decomposed model shown in equations (2.17) to (2.19). In the classical one-dimensional bin-packing problem, given that $L = (q_1, q_2, \dots, q_m)$ of items with sizes $s(q_1), s(q_2), \dots, s(q_m)$, the objective is to pack them using minimum number of unit-capacity bins. A survey on bin-packing problem is shown by Coffman Jr et al. (1996).

Consider an instance where

- The number of lane is $l \epsilon \{1,2, \dots, L\}$
- Shipper wants to ship α unit of loads in each lane and n carriers have same maximum capacity, β in each lane such that $\alpha \leq n\beta, \alpha > 0, \beta > 0$
- The unit price submitted by carriers is $p, p > 0$
- The carriers want all or nothing in each lane

From this instance, the decomposed model (in section 2.1.5) becomes:

$$\text{Min}\, F(\tilde{y}, \tilde{x}) \tag{2.23}$$

s.t.

$$-\sum_{c \in C} (\beta y^c) \leq -\alpha \qquad \forall\, l \tag{2.24}$$

$$y^c \in \{0,1\} \qquad \forall\, c \tag{2.25}$$

where $F(\tilde{y}, \tilde{x})$ is calculated by solving

$$F(\tilde{y}, \tilde{x}) = \text{Min}\, \beta p \sum_{k \in (c\, \cap\, y^k = 1)} x_l^k \tag{2.26}$$

s.t.

$$-\beta \sum_{k \in (C\, \cap\, y^k = 1)} x_l^k \leq -\alpha \qquad \forall\, l \tag{2.27}$$

$$x_l^k \in \{0,1\} \qquad \forall\, c \tag{2.28}$$

Notice that the capacity and submitted price is the same. To minimize the cost, the number of assigned packages is minimized. It is similar to bin-packing problem, which is minimizing the number of bins used. If $\tilde{y}^*$ and $\tilde{x}^*$ are optimal assignments of carriers for model shown in equations (2.23) to (2.28), then the shipment of the loads