

**A COMPARATIVE STUDY FOR PARAMETER  
SELECTION IN ONLINE AUCTIONS**



**GAN KIM SOON**

**UMS**  
UNIVERSITI MALAYSIA SABAH

**SCHOOL OF ENGINEERING AND  
INFORMATION TECHNOLOGY  
UNIVERSITI MALAYSIA SABAH  
2009**

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SELECTION IN ONLINE AUCTIONS**

**GAN KIM SOON**



**UMS**  
**UNIVERSITI MALAYSIA SABAH**

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**SCHOOL OF ENGINEERING AND  
INFORMATION TECHNOLOGY  
UNIVERSITI MALAYSIA SABAH**

**2009**

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## CERTIFICATION

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## **ABSTRACT**

### **A COMPARATIVE STUDY FOR PARAMETER SELECTION IN ONLINE AUCTIONS**

In this information-rich age, online auctions have become an important procurement tool in either commercial or personal use. As the number of auctions increases, the process of monitoring, tracking bid and bidding in multiple auctions become a problem. The user needs to monitor many auctions sites, picks the right auction to participate, and makes the right bid in making sure that the desired item satisfies the user's preference. All these tasks are somewhat complex and time consuming. The task even gets more complicated when there are different start and end times and when the auctions employ different protocols. Due to the complex and dynamic nature of the online auction, one of the strategies employed is using genetic algorithm to discover the best strategy. Hence, this work attempts to improve an existing bidding strategy by taking into accounts the evolution of various model of genetic algorithm in optimizing the parameter of the bidding strategies. In this work, three different models of genetic algorithms are considered. In the first model, the crossover and the mutation rate of the genetic algorithms are varied in order to create different combination of crossover and mutation rate. The new combination of genetic probabilities from this investigation will eventually perform better than the recommended genetic probabilities adopted in the previous work. The second model is the dynamic adaptation model namely the dynamic deterministic adaptive model. The bidding strategy from the experimental result of this experiment will eventually perform better than the bidding strategy that applied fixed static genetic operator's probabilities. Self-adaptation genetic algorithm is the last model that will be used to evolve the bidding strategy. The bidding strategies applying self-adaptation model are expected to perform better than the deterministic dynamic adaptation because of the nature of the algorithm itself. The evaluations are conducted in a simulated online auction framework with multiple auctions running concurrently. The effectiveness of the bidding strategies is measured based on the average fitness of the individuals, the success rate and average payoff in obtaining the item in the auctions. The performance of these bidding strategies will be empirically demonstrated in this thesis.

## **ABSTRAK**

*Dalam era teknologi maklumat maju kini, lelong dalam talian telah menjadi yang satu cara pembelian yang penting sama ada untuk komersial atau kegunaan peribadi. Disebabkan jumlah transaksi lelong yang kian meningkat, proses pengawasan, penjejakan bida dan proses pembidaan dalam pelbagai lelong menjadi satu masalah. Pengguna perlu memantau banyak laman-laman lelong, memilih lelong yang berpotensi untuk disertai, dan membida dalam lelong yang dapat memenuhi permintaan pengguna. Semua tugas-tugas tersebut adalah agak kompleks dan memakan masa. Tugas ini akan menjadi lebih kompleks apabila pelbagai lelong mempunyai perbezaan dalam masa permulaan dan masa tamat serta mengamalkan protokol berlainan. Oleh sebab sifat dinamik dan kompleks lelong talian, salah satu strategi adalah menggunakan algoritma genetik untuk memperolehi strategi terbaik. Justeru, projek ini adalah untuk meningkatkan strategi pembidaan yang sedia ada dengan mengambil kira kepelbagaian model evolusi algoritma genetik. Dalam projek ini, tiga model algoritma genetik diambil kira. Dalam model pertama, berbagai-bagai kadar penyilangan dan mutasi algoritma genetik dieksperimentasikan untuk memperolehi pelbagai gabungan kadar penyilangan dan mutasi serta bagi memilih gabungan terbaik yang boleh menjana keputusan terbaik. Kombinasi baru bagi kadar penyilangan dan mutasi dijangka yang diperolehi daripada eksperimen ini dijangka akan menjana keputusan yang lebih daripada kombinasi kadar penyilangan and mutasi yang lama. Model kedua adalah model adaptasi dinamik iaitu model penentuan adaptasi dinamik. Strategi pembidaan daripada keputusan eksperimen ini dijangka akan menjana keputusan yang lebih baik daripada strategi pembidaan yang mengaplikasikan kadar penyilangan and mutasi yang tetap. Adaptasi diri algoritma genetik merupakan model terakhir yang digunakan untuk mengevolusikan strategi-strategi pembidaan. Strategi pembidaan yang mengapikasi adaptasi diri adalah dijangka akan menjana keputusan yang lebih baik daripada strategi pembidaan yang mengaplikasikan adaptasi dinamik disebabkan oleh sifat algoritma sendiri. Kajian dikendalikan dalam simulasi lelong talian yang mempunyai pelbagai lelong yang dijalankan serentak. Keberkesanan strategi-strategi pembidaan adalah diukur berdasarkan kepada purata kesesuaian individu, kadar kejayaan dan purata keuntungan dalam memenangi item dalam lelong. Prestasi strategi pembidaan ini akan didemonstrasi secara empirikal dalam tesis ini.*



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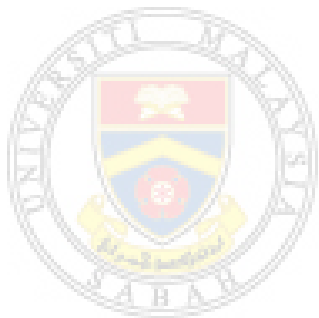
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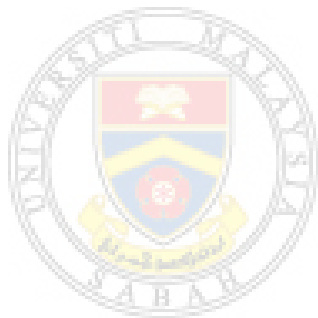


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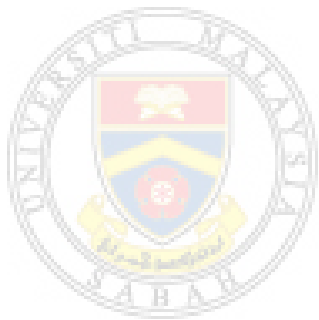
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## LIST OF ABBREVIATIONS

EA	Evolutionary Algorithms
E-Commerce	Electronic Commerce
GA	Genetic Algorithm
CFMD	Deterministic Decrease Mutation Rate
CFMI	Deterministic Increase Mutation Rate
CIMF	Deterministic Increase Crossover Rate
CDMF	Deterministic Decrease Crossover Rate
CDMI	Deterministic Decrease Crossover Rate with Deterministic Increase Mutation Rate
CDMD	Deterministic Decrease Mutation Rate with Deterministic Decrease Crossover Rate
CIMD	Deterministic Increase Crossover Rate with Deterministic Decrease Mutation Rate
CIMI	Deterministic Increase Crossover Rate with Deterministic Increase Mutation Rate
SACM	Self Adaptive Crossover and Mutation
SAC	Self Adaptive Crossover
SAM	Self Adaptive Mutation

## LIST OF SYMBOLS

$>$	Greater than
$<$	Less than
$\geq$	Greater than or equal to
$\leq$	Less than or equal to
$\Sigma$	Sum over
$=$	Equal to
$\in$	Is an element of
$\lambda$	Agent's bid increment value
$\sigma_i$	Auction starting time for auction $i$
$\eta_i$	Auction ending time for auction $i$
$S_i(t)$	Auction status for auction $i$
$p_c$	Crossover rate
$p_m$	Mutation rate
$p_r$	Private valuation
$v_i$	Wining for auction $i$
$L(t)$	Set of active auctions
$E(t)$	Set of active English auctions
$D(t)$	Set of active Dutch auctions
$V(t)$	Set of active Vickrey auctions
$f_{rt}$	The current bid value for remaining time tactic
$f_{ra}$	The current bid value for remaining auction tactic
$f_{ba}$	The current bid value for user's desire of bargain tactic
$f_{de}$	The current bid value for user's level of desperateness tactic

$k_{rt}$	Constant that determines the value of the starting bid for remaining time tactic
$k_{ra}$	Constant that determines the value of the starting bid for remaining auction tactic
$k_{ba}$	Constant that determines the value of the starting bid for user's desire of bargain tactic
$k_{de}$	Constant that determines the value of the starting bid for user's level of desperateness tactic
$\beta_{rt}$	The rate of concession to $p_r$ for remaining time tactic
$\beta_{ra}$	The rate of concession to $p_r$ for remaining auction tactic
$\beta_{ba}$	The rate of concession to $p_r$ for user's desire of bargain tactic
$\beta_{de}$	The rate of concession to $p_r$ for user's level of desperateness tactic
$w_{rt}$	The relative weight for the remaining time tactic
$w_{ra}$	The relative weight for the remaining auction tactic
$w_{ba}$	The relative weight for the user's desire of bargain tactic
$w_{de}$	The relative weight for the user's level of desperateness tactic
⊖	P value is more than 0.05, which means no significant improvement
⊕	P value is less than 0.05, which means significant improvement

## CHAPTER 1

### INTRODUCTION

#### 1.1 Introduction

Auction is defined as a bidding mechanism and is expressed by a set of auction rules that specify how the winner is determined and how much he or she has to pay (Wolfstetter, 2002). It has been used widely since 500 B.C whereby auctions were used by the ancient people to allocate scarce resources in Babylon (Shubik, 1983). The community was using auction to bid for their prospective wives and these bidding systems are still practiced in some of the places in Egypt. Moreover, the ancient Rome has been practicing auctions for commercial trading to liquidate property and to sell off leftover spoils of war at the battlefield. Since then, auctions have been practiced widely in the human civilizations where they were used to liquidate goods and to sell off the unsaleable goods. Throughout the years, auction has gained its popularity due to its effectiveness in allocating resources by the individuals who will value them the most (Reynolds, 1996). This effectiveness has brought about many variants of auctions, particularly the last few years (Wuman *et al.* 2001).

The traditional single-sided auctions can mainly be classified into four different types as follows (Klemperer, 1999).

- a) The ascending-bid auction (also called the open, oral, or English auction)
- b) The descending-bid auction (also called Dutch auction)
- c) The first-price sealed bid auction
- d) The second-price sealed bid auction (also called Vickrey auction (Vickrey, 1961))

English auction is the most common auction. In this type of auction, the auctioneer will start the auction with a low price which will then be successively raised up until only one bidder remains. The remaining bidder will be the winning bidder and thus, he or she will have to pay for the value of the item which

is equivalent to the bid value. This type of auction is executed in three different ways; by having the seller to announce the price, by having the bidders to call out the price themselves, or by having bids submitted electronically with the best latest bid posted at each stage of the auction. The bidders will have the chance to observe the latest high price posting while deciding either to continue bidding or to quit at any stage of the bidding. Once the bidder has decided to quit, he or she will not be allowed to rejoin the auction again. This type of auction can be commonly found in antiques, artworks and bidding auction house.

The descending bidding auction is the opposite of the ascending bidding auction. In a descending bidding auction, the auctioneer normally starts with a relatively high price and progressively lowers the price until a bidder calls to claim for the item. The winning bidder will be the first bidder who calls out for the item at the current price stated. This type of auction is known as the Dutch auction and is commonly used in Netherlands for selling flowers (van Heck & Ribbers, 1997). Similar auction is also used to buy and sell fish and tobaccos in many countries such as Spain, Israel and Canada (Klemperer, 1999).

The remaining two types of the auctions are called the sealed bid auctions. In sealed bid auctions, each bidder will submit their bids independently without knowing what the others' bid values are. The bids are opened when the auction is closed and the winner will be decided. In the first-price sealed bid auction, the winner will be the bidder with the highest bid and he or she will pay for a price equivalent to his bid value for the item. In contrast, the winner will only have to pay the price that is equivalent to the second highest bid instead of the highest bid in the second-price sealed bid auction. First-price sealed bid auctions are normally used in auctioning mineral rights in government owned land and also used sometimes in the sales of artworks and real estates (Klemperer, 1999) whereas the second-price sealed bid auctions are used for auctioning stamps, autographs and Civil War memorabilia by mail (Lucking-Reiley, 2000b; Rothkopf *et al.* 1990).

## 1.2 What is Online Auction?

Jansen defines an online auction as an Internet-based version of a traditional auction (Jansen, 2003). The advancement of the internet technology has brought a new method of trading, namely, the e-commerce. Any business transaction (buying and selling process) whose price or essential terms are negotiated over an online system such as the Internet, Extranet or Electronic Data Interchange network is called the E-commerce (or electronic commerce). In today's e-commerce market, online auction has acted as an important tool in the services for procuring goods and items either for commercialize purposed or for personal used. Online auctions have been reported as one of the most popular and effective ways of trading goods over the Internet (Bapna *et al.* 2001). Electronic devices, books, computer software, and hardware are among the thousands items sold in the online auctions every day. To date, there are 2603 auction houses that conduct online auctions as listed on the Internet (Internet Auction List, 2008). These auction houses conduct different types of auctions according to a variety of rules and protocols. eBay, as one of the largest auction house alone has more than 338.2 million registered users and had transacted more than USD15.68 billion worth of goods during the second quarter of 2008 (eBay, 2008). These figures clearly show the importance of online auctions as an essential method for procuring goods in today's e-commerce market.

The major difference between the traditional auction and online auction is the flexibility in conducting the auction. There are many limitations in a traditional auction setting. With the aid of online auction, many constraints that used to be in the traditional auction have now been diminished. Table 1.1 shows some of the differences between traditional auction and online auction.

**Table 1.1: Comparison between traditional auction and online auction**

Traditional Auction	Online Auction
The auctioneer and the bidders have to gather in one room at a given time to decide who gets the item and at what price.	The users just need to be in front of a personal computer with an internet connection to participate in an online auction that may be located in another part of the world (Lucking-Reiley, 2000a).
Auctioneers and bidders are required to come to the auction's venue. This practice limits many of the potential bidders that cannot attend the auction.	Online auction increases flexibility and ease the participation in auction for users, thus allowing the users to participate in an auction wherever they are and whenever they want.
Traditional auctions normally sell an item within a few minutes or even seconds. The rapid process with only limited time for the auction participants to make decision may cause many of them to pull out from bidding for the item in the auction. As a consequence, the sellers may not get the highest possible price for their goods (Turban <i>et al.</i> 2000).	The duration for online auctions lasts longer than traditional auctions, it normally lasts for days and weeks, and this allows the bidders to have more time to think and to decide when to submit their bids.
The goods to be auctioned may also cause problems in traditional auction because of the difficulty in transferring them to the auction site.	Online auctions allow sellers to sell their goods efficiently with little action or effort required.
A large cost is associated with operating the traditional auction since the sellers have to rent the auction site while the	In online auction, seller will only be required to set up a seller's account by filling up a seller's form detailing the