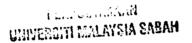
## PREDICTOR AGENT FOR ONLINE AUCTION CLOSING PRICE

## **LIM PHAIK KUAN**



# THESIS SUBMITTED IN PARTIAL FULFILLMENT FOR THE DEGREE OF MASTER OF SCIENCE

## SCHOOL OF ENGINEERING & INFORMATION TECHNOLOGY UNIVERSITI MALAYSIA SABAH 2009



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#### **ABSTRACT**

Online auction has given consumers a "virtual" flea market with all the new and used merchandises from around the world. Due to the increasing demand of online auction, consumers are faced with the problem of monitoring multiple auction houses, picking which auction to participate in, and making the right bid. If bidders are able to predict the closing price for each auction, then they are able to make a better decision on the time, place and the amount they can bid for an item. However, predict closing price for an auction is not easy since it is dependent on many factors such as the behaviour and the number of the bidders. This thesis investigates one of the methods used in predicting the closing price of an auction called the Grey System Theory. This method has been known to accurately speculate values in areas where the information is insufficient. Three other predictor methods are compared with Grey System Theory which are Time Series, Artificial Neural Network and Simple Exponential Function. These four prediction methods are then applied into different agent. The Grey System Agent is compared with other prediction agents namely the Time Series Agent, the Artificial Neural Network Agent and the Simple Exponential Function Agent. The effectiveness of these agents is evaluated using a simulated auction environment as well as real data obtained from eBay. In conclusion, Grey System Agent is able to predict well in simulated marketplace and eBay. Besides that, moving observation increased the performance of the prediction.



#### **ABSTRAK**

Lelong dalam talian telah memberi pengguna-pengguna satu pasar lambak "maya" dengan semua dagangan yang baru dan terpakai dari seluruh dunia. Disebabkan oleh penokokan permintaan lelong dalam talian, pengguna-pengguna bersemuka dengan masalah memantau rumah-rumah lelong, pemilihan lelong untuk disertai, dan memastikan bahawa mereka mendapat item tersebut sesuai dengan permintaan mereka. Jika pembida-pembida mampu untuk meramalkan harga penutup untuk tiap-tiap lelong, maka mereka mempunyai kelebihan daripada pembida-pembida yang lain, Bagaimanapun, meramal satu harga penutup untuk satu jualan lelong adalah bukan mudah memandangkan janya adalah bergantung kepada banyak faktor seperti kelakuan pembida dan jumlah pembida-pembida yang menyertai lelong itu. Tesis ini menjelaskan satu kaedah ramalan harga penutup satu jualan lelong yang dipanggil "Grey System Theory". Kaedah ini telah diketahui dapat meramal dengan tepat walaupun maklumat tidak mencukupi. Tiga kaedah-kaedah peramal yang lain dibandingkan dengan "Grey System Theory" yang adalah "Time Series", "Artificial Neural Network" dan "Simple Exponential Function". Ini empat kaedah-kaedah ramalan sedang kemudian memohon kepada ejen berbeza. "Grey System Agent" dibandingkan dengan ejen-ejen ramalan lain yakni "Time Series Agent", "Artificial Neural Network Agent" dan "Simple Exponential Function Agent" secara teratur. Untuk menguii keberkesanan ini agent-agent adalah dinilaikan menggunakan satu persekitaran lelong yang tersimulasi serta data sebenar yang diperolehi dari eBay. Dalam kesimpulan, "Grey System Agent" mampu meramalkan baik dalam persekitaran lelong yang tersimulasi dan eBay. Selain itu, data bergerak member keputusan yang lebih baik daripada data tetap,



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### LIST OF SYMBOLES AND ABBREVIATION

GSA Grey System Agent

GSAF Grey System Agent with Fixed Observations

GSAM Grey System Agent with Moving Observations

TSA Time Series Agent

TSAF Time Series Agent with Fixed Observations

TSAM Time Series Agent with Moving Observations

ARIMA Autoregressive Integrated Moving Average

ARMA Autoregressive Moving Average

ANNA Artificial Neural Network Agent

ANNAF Artificial Neural Network Agent with Fixed Observations

ANNAM Artificial Neural Network Agent with Moving Observations

SEFA Simple Exponential Function Agent

SEFAF Simple Exponential Function Agent with Fixed Observations

SEFAM Simple Exponential Function Agent with Moving Observations

- I<sup>TH</sup> ORDER ACCUMULATING GENERATION OPERATORS (AGO)

n - NUMBER OF OBSERVATION DATA

∑ - SUMMATION

t - TIME STEP

∀ - EVERY

*f* - INVERSE ACCUMULATING GENERATION OPERATORS (IAGO)

e - EXPONENTIAL FUNCTION

y<sub>t</sub> - VALUE FORECASTING AT TIME T

• PARAMETER FOR AUTOREGRESSIVE MODEL AT ORDER P

 $heta_q$  - PARAMETER FOR MOVING AVERAGE MODEL AT ORDER Q

 $\varepsilon_t$  - RESIDUAL AT TIME T

THE FIRST DIFFERENCE OF THE EXCHANGE RATE

Ø (B)
 AUTOREGRESSIVE OPERATOR

 $\theta$  (B) - MOVING AVERAGE OPERATOR

- LAG KAUTOCORRELATION FUNCTION (ACF)

 $\overline{y}$  - MEAN OF y

 $r_{kk}$  - PARTIAL AUTOCORRELATION FUNCTIONS (PACF) WITH

COEFFICIENT OF ORDER K

τ - NUMBERS OF PARAMETER

 $Q_{LB}$  - LJUNG-BOX TEST STATISTIC

n' - SAMPLE SIZE AFTER FIRST DIFFERENCE

number of lags being tested

ho(j) - RESIDUAL OF AUTOCORRELATION AT LAG j

**ESS** - SUM OF SQUARED ERRORS

k - TOTAL VARIABLE

NINPUT - NUMBER OF ELEMENT IN INPUT VECTOR

NHIDDEN LAYER - NUMBER OF NEURON IN HIDDEN LAYERS

NOUTPUT LAYER - NUMBER OF ELEMENT IN OUTPUT LAYERS

Noutput - NUMBER OF ELEMENT IN INPUT VECTOR

W - WEIGHT VALUE

B - BIAS VALUE

*F* - ACTIVATION FUNCTION

 $X_i$  - INPUT UNIT OF ANN, i = 1, ..., n

 $Z_j$  - HIDDEN UNIT OF ANN, j = 1, ..., p

 $Y_k$  - OUTPUT UNIT OF ANN, k = 1, ..., m

 $\delta_{\pmb{k}}$  - ERROR INFORMATION TERM

Δw<sub>ik</sub> - WEIGHT CORRECTION TERM

CONSTANT VALUE IN GREY SYSTEM PREDICTION MODEL



## LIST OF APPENDIX

Appendix A: Accepted Publications

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#### **CHAPTER 1**

#### INTRODUCTION

### 1.1. Overview

The word "auction" is derived from the Latin "aguere", which means "to increase" or "augment" (Krishna, 2002). Auction markets provide centralized procedures for the exposure of purchase and sale orders to all market participants simultaneously (Lee, 1996). In fact, auctions are not a new topic but have been widely used for centuries (Cassady, 1968). The design and conduct of auctioning institutions have caught the attention of many people over thousands of years. One of the earliest reports of an auction was that used to allocate scarce resources in Babylon from about five hundred B.C. (Shubik, 1983). During the closing years of the Roman Empire, auctions were used to sell everyday household objects, war spoils, or even tax collection rights. In China, the personal belongings of deceased Buddhist monks were sold at auctions as early as the seventh century A.D. (Paul and Robert, 1982). Auction is defined as a market institution with an explicit set of rules determining resource allocation and price on the basis of bids from the market participants (McAfee and Mcmillan, 1987). An auction is also defined as a bidding mechanism, described by a set of auction rules that specify how the winner is determined and how much he has to pay (Wolfstetter, 2002). Against this background, an online auction can be defined as an Internet-based version of a traditional auction. Online auction is one of the most popular and effective ways of trading by bidding for products and services over the Internet (Bapna et al., 2001). Nowadays, online auctions have become an increasingly popular and effective medium for transacting businesses as well, either procuring goods or services, both between individuals over the internet and between business and their suppliers. According to He et al., (2003), online auctions are increasingly being used for a variety of e-commerce applications. Online auctions are establishing the "true market value" and distribution of goods, property, and real estate to those who value it most highly. Today, online auction is an accepted media where bidders can compete equally and act in their own interest. They fill the buying and selling needs of thousands of people, products and properties all over the world. Objects as diverse as spectrum rights, treasury bills, and cars are regularly auctioned off. Since many products have their origin on the auction block, no one, regardless of financial

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status, can escape the effects of auction buying and selling in online auction. The utilization of online auction is widely emerging and becoming a popular business entity because of the flexibility and convenience that it offers to consumers. Online auction has given consumers a "virtual" flea market with all the new and used merchandises from around the world. They also give sellers a global storefront from which to market their goods. Compared to traditional auction, the globalization of internet auction has attracted more consumers to purchase various goods anywhere and anytime by just a click on their finger tip.

Over the last few years, a big number of online auction houses have emerged and the number is increasing rapidly. Some examples of popular online auction houses include eBay<sup>1</sup>, Amazon<sup>2</sup>, Yahoo!Auction<sup>3</sup> and UBid<sup>4</sup>. According to the internet auction list<sup>5</sup>, there are currently more than two thousand six hundred auction company listings around the world. The total revenue of the popular auction house e-Bay (in Figure 1.1) has increased by more than \$4.4 billion from 2004 (\$3,271,309) to 2007 (\$7,672,329). In addition, over ten million items can be found daily for sale at online auctions. Some of the examples are the antiques, books, electronic appliances, agricultural products and so forth. Online auctions continue to attract many customers, and currently sell goods worth over thirty billion USD annually (David *et al.*, 2005). In eBay alone, for example, there are often hundreds or sometimes even thousands of concurrent auctions running worldwide selling such substitutable items.



<sup>1</sup> http://www.ebay.com/

<sup>&</sup>lt;sup>2</sup> http://www.amazon.com/

<sup>3</sup> http://auctions.yahoo.com/

<sup>4</sup> http://www.ubid.com/

<sup>&</sup>lt;sup>5</sup> http://www.internetauctionlist.com/

C- 0 → eBay	y Inc. NASDAQ-68		<u>Learn Mo</u>	re About XBR
come Statements   Balance Shee	ts   Statements of C	ash Flow   Finar	icial Ratios	
Annual Income Statement (value)	in 000°s)		<u>Get Qı</u>	iaiterly Data
Period Ending:	12/31/2007	12/31/2006	12/31/2005	12/31/2004
Total Revenue	\$7,672,329	\$5,969,741	\$4,552,401	\$3,271,309
Cost of Revenue	\$1,762,972	\$1,256,792	\$818,104	\$614,415
Gross Profit	\$5,909,357	\$4,712,949	\$3,734,297	\$2,656,894
Operating Expenses Research and Development Sales, General and Admin.	\$619,727 \$3,081,408	\$494,695 \$2,598,220	\$328,191 \$1,835,458	\$240,647 \$1,291,078
Non-Recurring Items Other Operating Items	\$1,390,938 \$204,104	\$0 \$197,078	\$0 \$128,941	\$0 \$65,927
Operating Income	\$613,180	\$1,422,956	\$1,441,707	\$1,059,242
Add1 income/expense items	\$154,271	\$130,021	\$111,148	\$77,867
Earnings Before Interest and Tax	\$767,451	\$1,552,977	\$1,552,855	\$1,137,109
Interest Expense	\$16,600	<b>\$</b> 5,916	\$3,478	\$8,879
Earnings Before Tax	\$750,851	\$1,547,061	\$1,549,377	\$1,128,230
Income Tax	\$402,600	\$421,418	\$467,285	\$343,885
Minority Interest	\$0	(\$4)	(\$49)	(\$8,122
Net Income-Cont. Operations	\$348,251	\$1,125,639	\$1,082,043	\$778,22
Net Income	\$348,251	\$1,125,639	\$1,082,043	\$778,22
Net Income Applicable to Common Shareholders	\$348,251	\$1,125,639	\$1,082,043	\$778,223

Figure 1.1: Annual Revenue of eBay Auction House from 2004 until 20076

## 1.2 Online Auction

A question may be asked, "Why are auctions used rather than other selling devices such as posting a fixed price?" According to Cassady (Cassady, 1968), one of the answers is, perhaps that some products have no standard value. For example, the price of any catch of fish depends on the demand and supply conditions at a specific moment of time, influenced possibly by prospective market developments. Besides, for manuscripts and antiques too, price must be remade for each transaction. For example, how can one discover the worth of an original copy of antiques from Tang Dynasty except by an auction method? To date, many traditional auction businesses are moving into the online auctions space joining winners in this market place as a consequence of rapid growth of advance computer technology (Akula and Menasce, 2004). The major difference between these two types is the additional degree of flexibility, multiplicity as well as convenience in the way the online auction is conducted.

http://fundamentals.nasdaq.com/nasdaq\_fundamentals.asp?CompanyID=7098&NumPeriods=4&Duration=2&documentType=1&coname=eBay+Inc.&logopath=http%3A%2F%2Fcontent.nasdaq.com%2Flogos%2FEBAY.GIF&market=NASDAQGS&PageName=Company+Financials&selected=EBAY&symbol=EBAY&ads=1

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