Predicting Online Auction Closing Price Using Grey System Theory

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ABSTRACT

Online auctions are a very popular method to buy and sell items on the Internet. However, it is very dynamic in that it is very difficult to predict the winning bid of a given auction. There have been numerous studies to design a bidding strategy that can be utilized by bidders to ensure that they always win an auction. The closing price of an auction is not known and is dependent on several factors such as the number of auctions selling the same item, the number of bidders participating in that auction as well as the behaviour of every individual bidder. To top it up, there can be multiple auctions running concurrently at the same time. To participate in an online auction, one has to decide which auction to participate, how much to bid and when to bid. In most cases, this process is time consuming and does not always guarantee a winning bid. Knowing the closing price would definitely solve part of the problem. If the closing price of an auction is known, then bidder could then decide which auction to participate and at what price. This paper describes one technique to predict the closing price of an auction. This technique is called the Grey System Theory which has been known to be able to accurately predict values in areas where the information is insufficient. This paper also investigates the effectiveness and the accuracy of this theory when applied to online auctions. Some preliminary evaluations will be discussed.

1. INTRODUCTION

Auction is a market institution with an explicit set of rules determining resource allocation and price on the basic of bid from the market participants (McAfee & McMillan, 1987). Nowadays online auction is one of the most popular and effective ways of trading by participants bidding for products and services over the Internet (Bapna, Goes, & Gupta, 2001). 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.

Online auction allows clients to buy and sell items by means of auctions anytime and anywhere they like. Moreover, online auctions generally last for days and weeks giving the bidders more flexibility about when to submit bids. Compared with the traditional business type, internet auctions can be a co-effective way to test-market products in an online sales environment and to liquidate dated or overstocked merchandise especially for small business owners. Besides that, by using online auction, there is no geographical limitation since both sellers and buyers do their trading in a "virtual" environment and any transaction can be made through the online banking. Moreover, due to the relatively low price and wider scope of products and services, the online auctions have attracted many bidders in the trading process. At the same time, many sellers will be attracted to the online auction as it has attracted many potential consumers. Online auctions also allow sellers to sell their goods efficiently and with little action or effort required.

There are four main types of single-sided auctions that are commonly used in traditional auctions (Klemperer, 1999) namely ascending-bid auction (also called the open, oral, or English auction), descending-bid auction (also called Dutch auction), first-price sealed bid auction and second-price sealed bid auction (also called Vickrey auction). The English begins with the lowest price and bidders are free to raise their bid successively until there are no more offers to raise the bid. Bidder with the highest bid is the winner. A Dutch auction is the opposite of an English auction, in which auctioneer begins with an initial high price and then progressively lowered until there is an offer from a bidder to claim the item. In the first price sealed bid, each bidder submits their offer for an item privately. The highest bidder gets the item and payment is based on their own bid. The Vickrey auction is similar to the first-price sealed bid auction, where the item goes to the highest bidder but he only pays a price equal to the second highest bid. Online auctions are somewhat similar to the traditional auctions but most auctions are constrained by the time. Auctions usually last for days and week depending on the seller's requirement.

Due to the proliferation of these online auctions, consumers are faced with the problem of monitoring multiple auction houses, picking which auction to participate in, and making the right bid to ensure that they get the item under conditions that are consistent with their preferences (Anthony & Jennings, 2003). These processes of monitoring, selecting and making bids are time consuming. The task becomes even more challenging when the individual auctions have different start and end times. Moreover, auctions can last for a few days or even weeks. Besides that, every bidder has his own reservation price or maximum amount that he is willing to bid for each item. If bidders are able to predict the closing price for each auction then they can make better decision on when and where or even how much they can bid for an item. In a situation where a bidder has to decide among the many auctions that are currently ongoing, this knowledge on closing price for an auction would be useful for the bidder to decide on which auction to participate, when to participate and at what price. There are other considerations that need to be taken into account to ensure that the bidder wins in a given auction. However, knowing the closing price of a given auction would definitely be an advantage because the bidder can decide where to bid and how much to bid. Unfortunately, predicting a closing price for an auction is not easy since it is dependent on many factors such as the behavior of the bidders and the number of bidders participating in that auction.

For these reasons, many investors have been trying to find a better way to predict auction closing price accurately. Neural Network, Fuzzy Logic, Evolutionary Computation, Probability Function and Genetic Algorithm, are integrated to become more commendable practical model for prediction purpose. However one particular method is to apply the Grey System Theory to predict online auction. It is a new theory and method which applies to the study of unascertained problems with few or poor incoming information (Liu & Lin, 2004). In online auction, the number of available information is limited and it is often very difficult to predict the outcome of an auction since bidders have different behavior. It is quite possible to predict the closing price of an auction using Grey Theory method and this will be elaborated in Section 4.

In this paper, we will investigate the effectiveness of the grey system theory in predicting the closing price of online auction. In Section 2, the design of grey theory system is explained. Section 3 discusses the prediction algorithm by using the grey system theory. The preliminary result is shown in Section 4. In section 5 some related works using grey theory are discussed and finally the conclusion and future work is discussed in Section 6.

2. GREY SYSTEM THEORY DESIGN

The grey system theory was first proposed by Deng Julong (1982). Grey system theory works on unascertained systems with partially known and partially unknown information by drawing out valuable information, by generating and developing the partially known information. It can describe correctly and moni-

Table 1. Attributes of traditional forecasting model

Mathematical model	Minimum observation	Type of sample	Sample interval	Mathematical requirements
Simple exponential function	5-10	Interval	Short	Basic
Regression analysis	10-20	Trend	Short	Middle
Casual regression	10	Any type	Long	Advanced
Box-Jenkins	50	Interval	Long	Advanced
Neural network	Large number	Interval or not	Short	Advanced
Grey prediction model	4	Interval	Long	Basic

tor effectively the systemic operational behaviour (Lin & Liu, 2004). Basically, the Grey system theory was chosen based on color. For instance, "black" is used to represent unknown information and "white" is the color used for complete information. Those partially know and partially unknown information is called the "Grey System Theory".

The grey system theory has been successfully applied to economical, management, social systems, industrial systems, ecological systems, education, traffic, environmental sciences, and geography (Lin & Liu, 2004). It is used successfully to analyse uncertain systems that have multi-data inputs, discrete data, and insufficient data. Grey systems theory explores the law of subject's motivation using functions of sequence operators according to information coverage. It is different from fuzzy logic since it emphasizes on objects with definite external extensions and vague internal meanings. Table 1 shows the Grey prediction model compared to other traditional forecasting models (Chiang, Wu, Chiang, Chang & Wen, 1998). It can be seen that this model only requires short-term, current and limited data in order to predict a given value.

Grey prediction is a quantitative prediction based on grey generating function, GM (1, l) model, which uses the variation within the system to find the relations between sequential data and then establish the prediction model. The grey forecasting model is derived from the grey system, in which one examines changes within a system to discover a relation between sequence and data. After that, a valid prediction is made to the system. Grey prediction model has the following advantages: (a) It can be used in situations with relatively limited data down to as little as four observations, as stated in Table 1. (b) A few discrete data are sufficient to characterize an unknown system. (c) It is suitable for forecasting in competitive environments where decision-makers have only accessed to limited historical data (Chiou, Tzeeng, Cheng & Liu., 2003).

3. GREY SYSTEM THEORY PREDICTION ALGORITHM

In this section we focus on the grey generating function, GM (1,1) which are being used in grey prediction (Deng & David, 1995). The algorithm of GM (1,1) can be summarized as follows.

Step 1. Establish the initial sequence from observation data

$F^{(0)} = \{f^{(0)}(1), f^{(0)}(2), \ldots, f^{(0)}(n)\}$.

Step 2. Generate the first-order accumulated generating operation (AGO) sequence

$F^{(1)} = \{f^{(1)}(1), f^{(1)}(2), \ldots, f^{(1)}(n)\}$.

where $f^{(1)}(k) = \sum_{i=1}^{k} f^{(0)}(i)$.

Step 3. The grey model GM (1,1)

$$F_{t+1}^{0} = a\left[-\frac{1}{2}\left(F_{t=1}^{1} + F_{t}^{1}\right)\right] + b, \qquad \forall t \geq 1.$$

Step 4. Rewrite into matrix form

$$\begin{bmatrix} F_2^0 \\ F_3^0 \\ \vdots \\ F_x^0 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\left(F_2^1 + F_1^1\right) & 1 \\ -\frac{1}{2}\left(F_3^1 + F_2^1\right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left(F_x^1 + F_{x-1}^1\right) & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}.$$

Step 5. Solve the parameter a and b

$$\hat{a} \text{ or } \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T F.$$

Step 6. Estimate AGO value

$$\hat{f}_{T+1}^{1} = \left[f_1^0 - \left(\frac{b}{a}\right)\right] e^{-a} + \left(\frac{b}{a}\right), \qquad \forall t \geq 1.$$

Step 7. Get the estimate IAGO value

$$\hat{f}_t^0 = \hat{f}_t^1 - \hat{f}_{t-1}^1, \qquad \forall t \geq 2$$

We use the average residual error for each set of data to calculate the accuracy of the predicted data. The formula for the average residual error is given as

$$\frac{1}{n}\left(\sum_{t=1}^{n} \frac{\left|f_t^0 - \hat{f}_t\right|}{f_t^0}\right).$$

Where f_t^0 = Original data at time t

$\hat{f}$ = Predicted data at time t

n = The total number of data has been predicted

In order to test the effectiveness of grey system theory, we set up an electronic simulated marketplace. The simulated electronic marketplace consists of a number of auctions that run concurrently. There are three types of auctions running in the environment: English, Dutch and Vickrey. The English and Vickrey auctions have a finite start time and duration generated randomly from a standard probability distribution, the Dutch auction has a start time but no pre-determined end time. At the start of each auction (irrespective of the type), a group of random bidders are generated to simulate other auction participants. These participants operate in a single auction and have the intention of buying the target item and possessing certain behaviour. They maintain information about the item they wish to purchase, their private valuation of the item (reservation price), the starting bid value and their bid increment. These values are generated randomly from a standard probability distribution. Their bidding behaviour is determined based on the type of auction that they are participating in. The auction starts with a predefined starting value; a small value for an English auction and a high value for a Dutch auction. There is obviously no start value for a Vickrey auction. The marketplace is flexible and can be configured to take up any number of auctions and any value of discrete time. We assume that all the auctions in the marketplace are auctioning the item that the consumers are interested in. Our bidder agent is allowed to bid in any of the auctions at any time when the marketplace is active. It is also assumed that all auctions are selling the same item.

4. PRELIMINARY EXPERIMENTAL EVALUATION

The purpose of this experimental evaluation is to determine the efficiency and accuracy of the grey system theory in predicting the closing price of an online auction. However, to calculate the prediction accuracy of this model, we worked on the original data taken from eBay financial result (eBay, 2006), the GAAP

Diluted EPS and pro-forma Diluted EPS data between the first quarters of 2005 until the second quarter of 2006. We used four historical data to calculate the predicted value. To test the accuracy of the grey theory, the accuracy is calculated based on the residual error. It was found that the average residual error for the GAAP predicted data is 3.91% (96% accuracy) and the non GAAP or Pro-forma is 2.99% (97% accuracy). This is very promising considering the fact that only four historical data are used in the prediction.

The next step however is to investigate whether we will get similar result when we apply this theory to predict the closing price of an online auction. Using the simulated marketplace, we ran the auction from t = 1 until t = 30. We have also set most of auctions to close after t = 15. In one particular run, the closing price history for all auction running in a marketplace are shown from t = 18 until t = 25. Our first experiment is to calculate the predicted auction closing price based on three, four, five, six, seven and eight historical closing price data which is shown in Table 3. The result of the prediction is shown as below. In can be seen that the average residual error falls between 3.58% to 29.12% and the highest accuracy is using 5 historical data.

At the same time, we also calculated the predicted closing price for five more data from t = 19 to t = 30 which is shown in Table 4. It was found that the average residual error increased to a range between 4.95% to 23.88%. This result is still acceptable since the average residual error is 9.09% (or 90% accuracy). In this case, the highest accuracy is using 4 historical data. It can also be seen in both experiment that the accuracy at the highest between 5 and 6 historical data.

In the following experiment, six moving historical data were used to predict the auction closing price. That means, to predict the auction closing price at t = 24, we will use data from the last five closing (t = 18 until t = 23). We used six historical data because of its performance in the previous experiment. Table 5 shows the predicted values based on the given range. In this particular experiment, the average residual error is between 4.30% to 26.11% and the average residual error for the 5 readings is 9.85% (90%). This experiment also shows that using moving historical data, grey theory is able to predict the auction closing price more accurately by just making use of six previous data. The result of these experiments shows that grey system theory can be used to predict the auction price of an auction. The difference between actual data and original data may be contributed by other factors such as bidder's emotion, the priority of the items, and so on, which are not taken into the consideration at this point.

5. RELATED WORK

There are many researches that have been engaging in the prediction and forecasting of real world phenomenon. Chiou et al. (2003) introduced Grey Prediction Model (GPM) to plan material of spare parts equipment in Taiwan. They took three types of weapon system periodic items of planning material from 1999 to 2002, and applied GM (1,1) model to predict the planning requirement of impenitent spare parts of 2003. Through this study, they demonstrated that the GM (1,1) produced a high level of accuracy in prediction of spare parts. Lin and Lin (2004) used grey prediction to improve the efficiency of achieving accurate and speedy inspection when a coordinate measuring machine (CMM) is used to measure circularity geometric tolerance. Grey theory was applied in developing the heuristic algorithm for predicting the number of measuring points required for measuring circularity geometric tolerance. The heuristic algorithm was used to plan the number of measuring points of the next work piece and to predict the circularity geometric tolerance dimensions. This step provides a better foundation for on-line inspection to determine the number of measuring points required for measurement inspection of the next work piece. It can also predict whether the circularity geometric tolerance of the next work piece will conform to the circularity geometric tolerance dimension on the design drawing. This heuristic algorithm could also be used to

Table 2. Result performed by using Grey prediction model compared with original data collected from eBay financial result

Year and Quarter	GAAP Original Data (Million)	GAAP Predicted Data (Million)	Pro Forma (non GAAP) Original Data (Million)	Pro Forma (non GAAP) Predicted Data (Million)
2005 Q1	256.3	-	275.5	-
2005 Q2	291.6	281.939	307.2	291.989
2005 Q3	255	264.068	280.2	293.533
2005 Q4	279.2	280.132	340.1	339.796
2006 Q1	284.3	264.074	342.9	344.893
2006 Q2	250	236.932	351	366.999

The average residual error of GAAP Predicted Data is 3.91%
The average residual error of non GAAP or Pro Forma Predicted Data is 2.99%

Table 3. Result performed by using Grey prediction model compared with original data generated by agent auction

Time (t)	Original Data	Using 3 Historical Data	Using 4 Historical Data	Using 5 Historical Data	Using 6 Historical Data	Using 7 Historical Data	Using 8 Historical Data
18	83	-	-	-	-	-	-
19	85	84.991	85.959	83.085	82.032	83.658	82.315
20	82	81.982	80.783	79.591	78.544	80.445	78.617
21	73	79.080	72.911	77.550	77.541	78.401	76.919
22	83	82.385	68.748	82.989	85.024	83.568	83.232
23	82	72.999	49.673	76.938	81.999	76.986	78.571
24	69	62.014	27.036	69.425	79.467	69.695	76.945
25	81	61.523	13.162	75.478	89.432	73.732	81.368

The average residual error of using 3 historical data is 7.75%
The average residual error of using 4 historical data is 29.12%
The average residual error of using 5 historical data is 3.58%
The average residual error of using 6 historical data is 5.99%
The average residual error of using 7 historical data is 3.95%
The average residual error of using 8 historical data is 4.15%

Table 4. Result performed by using Grey prediction model compared with original data generated by agent auction

Time (t)	Original Data	Using 5 Historical Data	Using 6 Historical Data	Using 7 Historical Data	Using 8 Historical Data
18	83	-	-	-	-
19	85	83.085	82.032	83.658	82.315
20	82	79.591	78.544	80.445	78.617
21	73	77.550	77.541	78.401	76.919
22	83	82.989	85.024	83.568	83.232
23	82	76.938	81.999	76.986	78.571
24	69	69.425	79.467	69.695	76.945
25	81	75.478	89.432	73.732	81.368
26	83	62.125	86.897	64.134	75.85
27	81	55.391	81.866	50.938	67.41
28	76	44.303	78.341	38.181	60.04
29	83	36.888	79.325	28.897	56.77
30	70	21.169	72.823	11.12	45.61

The average residual error of using 5 historical data is 18.10%
The average residual error of using 6 historical data is 4.94%
The average residual error of using 7 historical data is 23.88%
The average residual error of using 8 historical data is 11.83%

determine whether the manufacturing process requires modification, in order to save human and material resources and reduce failure rate.

Wang (2002) used the fuzzy grey prediction system to predict the stock price instantly at any given time. Wang combined fuzzification techniques with grey theory to develop a fuzzy grey prediction and plugged it into a system to predict the possible answer immediately. He used the prediction system to analyze stock data and to predict the stock price promptly at a specific time. Wang, Chang, Belkasim and Sunderraman (2002) designed the real time fuzzy personalized stock information agent based on fuzzy logic. The smart agent enables the users to create their own portfolios that contain the real time watch list of personalized stocks. This application enables the user to get accurate, real time information of a pre-selected list of favourite stocks. Using fuzzy reasoning, the Web stock agent is capable of ranking the "top 10 stocks" based on their real time stock information. Since output values are calculated with the consideration of degree of uncertainty, results of the data process are precise and reliable. It saves time for user to search for stock information, and good stocks from thousands of stocks.

Hassan, Nath and Kirley (2006) proposed and implemented a fusion model by combining the Hidden Markov Model (HMM), Artificial Neural Networks (ANN) and Genetic Algorithms (GA) to forecast financial market behaviour. The tool can be used for in depth analysis of the stock market. Using ANN, the daily stock prices are transformed to independent sets of values that become the input to HMM. They drew on GA to optimize the initial parameters of HMM. The trained HMM is used to identify and locate similar patterns in the historical data. The price differences between the matched days and the respective next day are

Table 5. Result performed by using Grey prediction model compared with original data generated by agent auction

Time (t)	Original Data	Using 1-6 Historical Data	Using 2-7 Historical Data	Using 3-8 Historical Data	Using 4-9 Historical Data	Using 5-10 Historical Data
18	83	-	-	-	-	-
19	85	83.085	-	-	-	-
20	82	79.591	81.152	-	-	-
21	73	77.550	78.592	77.199	-	-
22	83	82.989	83.357	81.591	79.813	-
23	82	76.938	76.481	76.176	76.517	76.733
24	69	69.425	68.9995	71.956	74.117	72.695
25	81	75.478	72.946	80.931	84.61	82.905
26	83	62.125	63.353	78.1	82.996	82.384
27	81	55.391	50.255	73.466	79.276	81.153
28	76	44.303	37.682	71.027	77.449	83.231
29	83	36.888	28.665	91.785	80.517	91.634
30	70	21.169	11.235	69.741	76.478	94.4

The average residual error of using 1-6 historical data is 4.94%
The average residual error of using 2-7 historical data is 26.11%
The average residual error of using 3-8 historical data is 5.21%
The average residual error of using 4-9 historical data is 4.30%
The average residual error of using 5-10 historical data is 8.73%

calculated. Finally, a weighted average of the price differences of similar patterns is obtained to prepare a forecast for the next day.

6. CONCLUSION AND FUTURE WORK

This paper elaborated on the used of grey theory system to predict the closing price of an online auction. It has been shown that using this method, the accuracy rate always exceed 90%. This closing price knowledge can then be used by the bidder to decide which auction to participate, when and how much to bid. This information will also allow the bidder to maximize his chances of winning in an online auction. For future work, we will continue to investigate the effectiveness of grey theory in multiple auctions. Work need to be done to incorporate more than six historical data for prediction. It would be desirable if we can take into account all the historical data to produce an even more accurate prediction. Apart from that, we would also look into combining the grey method with other AI techniques.

In a larger context, this information about the closing price will be made use to support the development of bidder's strategies in online auction (Anthony & Jennings, 2003). Given a situation in which there are more than one potential auctions that the agent can participate, it would need to decide which auction it should participate in order to guarantee that it gets the item at the best price. In this case, the best price is the bid value that is less than the agent's reservation price. If the agent can predict the closing price accurately for each potential auction, then it would be able to make a quick decision on which of these potential auctions it should participate to maximize its gain.

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