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An Application of Artificial Neural Network to Support Decision Making in Bilateral Negotiation

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This study focus on the bidding strategy in the negotiation process particularly in the supply chain field. Bilateral negotiation has an important role in process to design an efficient supply contract since choose the wrong supplier will be highly cost. The negotiation is a process of making decision in iteration way. The participants will take into account which strategy they should address in each round. The present of intelligent agent in negotiation process had significant interest these days. As making decisions using a rational strategy still difficult for negotiators according to two-sided uncertainty and bargaining power in bilateral negotiation, by means of neural network, agent equipped with capability to learn from past negotiation and support in deciding appropriate negotiation strategy. This study attempts to develop an artificial neural network predictive model. The simulation was used to exhibit negotiation process between buyer and supplier. The Levenberg–Marquardt algorithm has been used to train the neural network and shown the good performance. The experiment was conducted to identify main factor in negotiation process and develop the proper bidding strategy. The advantage of this work over earlier research is in ability to short the negotiation round which is increase the negotiation efficiency.

Keywords: *bilateral negotiation, concession strategy, artificial neural network.*

1. Introduction

Supply contract is a way to occupy the uncertainty in demand and price, the successful of long-term business in buyer-supplier relationships relies on the negotiation process and relationship building. The experience of senior manager supported by technical information required due to successful negotiation.[1] Considering a number of issue in negotiation process e.g. price, duration, cost, etc., therefore a way to understanding the negotiating process is by examining the techniques that might help in predicting the outcomes of negotiations. An accurate predictions of the outcomes of marketing negotiations can help parties to develop better strategies.[2] The learning process from past negotiations can be achieve through intelligent agent which attempt to assist in selecting appropriate negotiation tactics. Machine learning, fuzzy expert system, data mining, neural network are some techniques commonly utilized to find useful applications in the context of electronic negotiations.[3]

Purchasing plan is the key point to cope with uncertainty in price and demand. Since the market price can be quite volatile, it prefer for buyer to bind in short-term contract. Two-sided bidding process can be developed between buyer and supplier while each party has an opportunity to send the bids and ask to determine the price.[4, 5] The simplest form of negotiation involves two parties and a single-issue.[6] Bilateral negotiation has an important role in process to design efficient supply contract, since choose the wrong supplier will be highly cost.[7] Either buyer or supplier both are frequently faced with difficult decisions that cannot be made using a rational strategy according to the bargaining power and two-sided uncertainty. A deadlock could happen in situation which both parties refuse to make concessions.

2. Experimental Design

In this section, the application of neural network is inserted into bilateral negotiation framework. The bidding negotiation starts when buyer sends the order to the supplier. The supplier bids for the contract by offering a price and the buyer then responses to this price by submitting a counter-offer at each round. Lets $p_s(t)$ and $p_b(t)$ denote the price offered by the seller and the buyer at the t^{th} round of the negotiation, respectively. Then the process of negotiation can be characterized by the sequence of offers and counteroffers, until the negotiation finished or failed in certain finite round.

The negotiation initiated as supplier offers the price for the certain quantity and due date placed by buyer. The price of supplier offer will be fluctuated from time to time since the bid price dependent each other round by round during the negotiation process then we called the strategy for both parties are the interactive bidding. The strategy for both supplier and buyer strategy are adopted from,[8] and established as following: $p_s(t) = \left[1 + k_s(t) - k_s(t)\left(\frac{t-1}{t^{max}-1}\right)^{\frac{1}{\beta_s}}\right]\mu_s,\ t\ 1, 2, \ldots, t^{max}$ Where $\boldsymbol{k_s(t)}$ and $\boldsymbol{\beta_s}$ are two decision parameters of supplier s. $\boldsymbol{k_s(t)} \geq 0$ denotes the marginal profit of its reservation price ($\boldsymbol{\mu_s}$) and related to the price concession rate of buyer, whereas $\boldsymbol{\beta_s}$ controls the shape of bid prices curve and responds to the negotiation concept such as negotiation power or time pressure. The negotiation power and time pressure of suppliers are depend on quantity and due date offered by demander, and the level of inventory, and also the scheduled plan of itself. The value of $k_s(t)$ is depend on the level of inventory and the bid prices of the buyer and will varied as negotiation process proceeds round by round. However, $\boldsymbol{\beta_s}$ keeps fixed at all negotiation rounds in a given session. For the buyer the bidding strategy is established as following:

$p_b(t) = \left[k_b(t) + (1 - k_b(t))\left(\frac{t-1}{t^{max}-1}\right)^{\frac{1}{\beta_b}}\right]\mu_b,\ \mathrm{t} = 1, 2, \ldots, t^{max}$. In supplier bidding strategy, $\boldsymbol{k_b(t)}$ and $\boldsymbol{\beta_b}$ are two decision parameters of buyer. $\boldsymbol{k_b(t)} \leq 1$ corresponds to the reservation price ($\boldsymbol{\mu_b}$) and related to the price concession rate of supplier, whereas $\boldsymbol{\beta_b}$ controls the shape of buyer's bid prices curve and responds to the negotiation concept such as negotiation power of time pressure. At the beginning of negotiation, buyer manipulates the values of $\boldsymbol{k_b(t)}$ and $\boldsymbol{\beta_b}$ in order to achieve its expected objective. In most cases, suppliers are reluctant to share cost information, except for information that is indirectly released through bilateral negotiations in which transaction prices are set.[9] However, the supplier's cost structure will influence by inventory cost, integration and cooperation costs. The fluctuation in supplier pricing will depend on the production condition and cost structure, $k_s(t) = \max\left\{k_s(t-1)\left\{1 + \theta_s\left[\frac{p_b(t-1) - p_b(t-2)}{p_b(t-2)}\right]\right\}, 0\right\}\ t = 3, 4, \ldots, t^{max}$, where θ_s is the adjusted coefficient of supplier.

At the time buyer put an order, the inventory status of supplier also unknown. Situated in this uncertainty will influence the tactics used in negotiation process. The buyer reservation price calculated as follows:

$k_b(t) = \min\left\{k_b(t-1)\left\{1 + \frac{\theta_b}{\sum_{s \in S} ql_s}\left[\sum_{s \in S} ql_s \frac{p_s(t) - p_s(t-1)}{p_s(t-1)}\right]\right\}, 1\right\}, t = 2, 3, \ldots, t^{max}$, where θ_b is the adjusted coefficient of buyer, and ql_s denotes quality level of supplier.

In this paper, the application of ANN in negotiation is extend to the supply contract field, particularly, in predicting opponent's price in bilateral negotiation between buyer and supplier. The artificial neural network-based (ANN) predictive model is developed under the following assumptions:

- The model purpose is for predicting the opponent next offer.
- Supplier offer the bid price first then buyer makes the counter-offer.
- The information offers between buyer and supplier only in purchasing request order.

The ANN-predictive model is designed as 9-13-1 multilayer perceptrons (MLPs) architecture. The number of neurons in input layer is as much as the number the number of available input information. The number of neurons in hidden layer is set to one which gives the minimum generalization error.[10] Through the trial and error experiment, the accuracy rate of each configuration is calculated by mean square error (MSE) function, average squared error between the network output, *a* and the target outputs, *t*. The output layer has one neuron which represents the predict price.

For using in ANN model, we randomly split up the bid price data. As many as 6615 (70%) of the record data were randomly selected for training the network, and the remaining 2835 (30%) were kept for testing the network. The Levenberg–Marquardt (LM) algorithm approximates to the Newton method and has been used for training ANN predictive model. The neural networks modeling and training in this work is performed in MATL AB 7.0.

3. Results and Discussion

To predict the opponent's price, either buyer predicted price ($\hat{p}_b(t)$) or seller predicted price ($\hat{p}_s(t)$) for each round, the best model is selected on the basis of their performance. The predictive ability of each model on unseen data (i.e. 30% testing data) can be identified by the model performance in term of R (R^2). The plot of target and network output for the round 4 in Figure. 1(a) shows a very good pattern with R^2= 0.997921 demonstrating that the model has the ability to predict well. Figure 1(b) shows as the maximum number of training epoch is set to be 1000, and the ANN-model stop trained at epoch 148 with MSE= 0.0007022, it is convinced that over fitting problem does not exist.

In order to provide the better strategy and tactics for the parties, we examined the negotiation process to identify any factors could have the main effect to the negotiation round. A five–factor experiment was conducted and as many as 625 experiments were run as each factor has five levels. Analysis of variance (ANOVA) was used to test the hypothesis about the differences between the success negotiations round. Based on the main effect and the interaction revealed by ANOVA, we can derive the strategy to be employed in the negotiation. However, there were several significant interactions between factors, due date and inventory (p =0.002), due date and $\boldsymbol{\beta_b}$ (p = 0.000), due date and $\boldsymbol{k_b}$ (p = 0.000), $\boldsymbol{k_b}$ and Inventory (p = 0.000) and the interaction between $\boldsymbol{k_b}$ and $\boldsymbol{\beta_b}$ (p = 0.000).

We investigate the interaction among factors to provide the strategy employed in the negotiation round. It is obviously seen in Figure 2. In the longest due date, the negotiation round reduce sharply when the value of k_b increase from 0.5 to 0.6, unless for the rest value, the negotiation is finished in the shorter round. The interaction between β_b and k_b is revealed that for the lower value of β_b the round reduce sharply as the value of k_b increased. However, as the value of β_b is high, the negotiation will concede faster at the beginning round. Increasing value of k_b no more reduce the round.

4. Conclusion

In this paper, we have presented a neural network- based predictive model. The model can be applied for support parties with useful information for predicting opponent's offer during negotiation process. The testing data has a very good and highly significant performance. Through the case application, ANN predictive model demonstrates attractive negotiation strategies, and the important thing is it provides useful information to the negotiator. Finally, further research can be extended to investigate how well is the proposed model performs in negotiation process between multi suppliers or buyers.

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Figure captions:

Figure 1. Scattered plot: (a) target vs. ANN outputs P̂s (t); (b) The best performance of ANN for training, validation and testing

Figure 2. The relations among factors (a). Interaction between $\boldsymbol{k_b}$ and due date (dd), (b). Interaction between Bb and $\boldsymbol{k_b}$

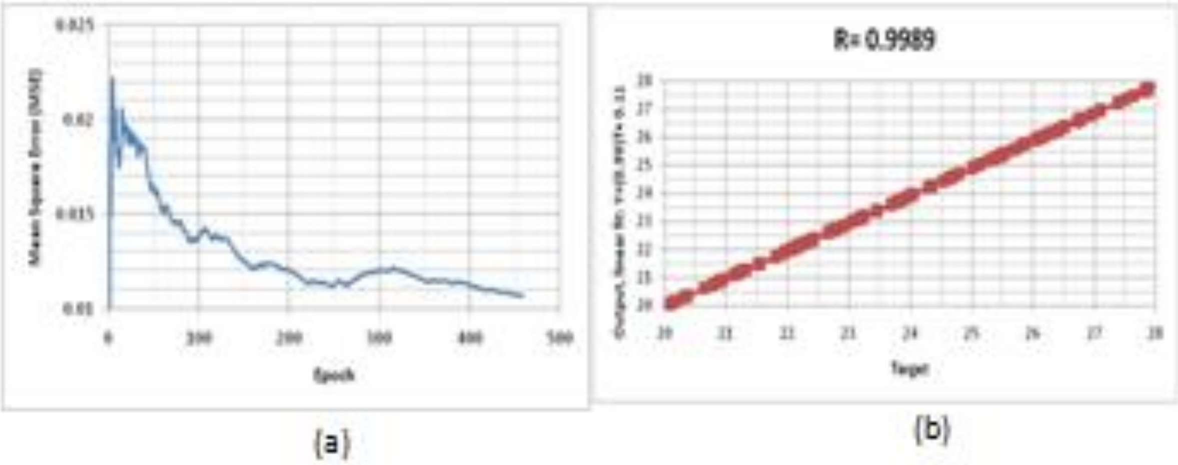

Figure 1. Muharni et al.

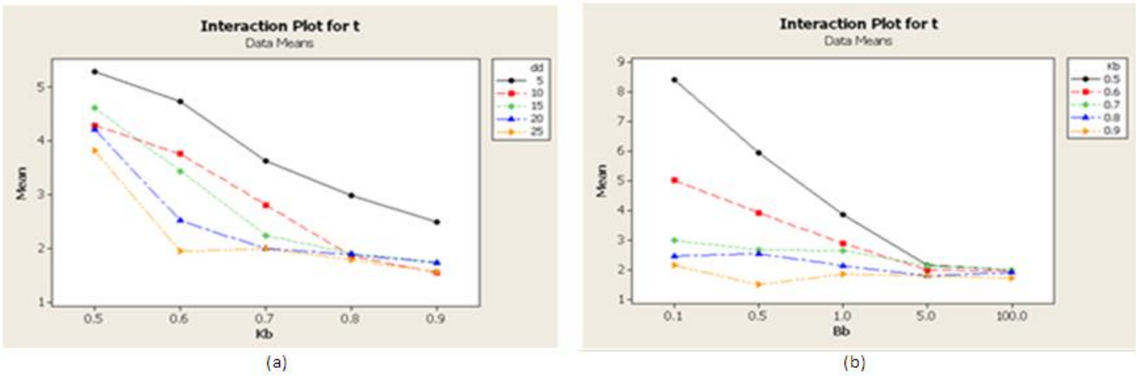

Figure 2. Muharni et al.