# A Real World Trading Oriented Market-driven Model for Negotiation Agent

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## Abstract

*Sim proposed a market-driven negotiation agent model that makes adjustable amounts of concession by reacting to different market situations and trading constraints in [1] and [2]. We improved Sim's model with an enhanced market-driven strategy that takes opponent eagerness into consideration in [3]. In both Sim's original model and our modified model, however, it was implied that a negotiation agent has same behaviors and actions to all trading partners referring to a same trading issue. It is not quite true in a real world trading negotiation. Based on Sim's and our previous modified model, this paper proposes a revised market-driven model that takes each trading partner as an individual with different strategies and actions. Moreover, negotiation actions between a negotiation agent and a trading partner are kept in secret and unknown to others.*

## 1. Introduction

With advanced developments of web technologies and network communications, e-commerce has being widely used. It has become an important driving force of the world economy. Same as in conventional commerce, one of the most crucial processes in e-commerce is negotiation, trying to reach a consensus on pricing and other terms of transactions. There are two styles in a negotiation process, that is, either a human user directly involved negotiation or an agent mediated automated negotiation [4]. The latter can reduce the transaction costs considerably and relieve human users from a time consuming and tedious process as well [5][6]. Based on a reasonable good model, agents might be better than human users at finding solutions to combinational optimizing problems [7]. That is to say, an agent mediated automated negotiation requires a model that can reflect human users' negotiation process.

Sim proposed a market-driven negotiation model that makes adjustable amounts of concession by reacting to different market situations and trading constraints. And furthermore, we improved Sim's model by introducing the learning of opponent eagerness. Although the improved model gave a reasonable good performance in the case of one-to-one negotiation, it is not so in the case of one-to-many or many-to-many negotiation, that is, a negotiation agent is conducting a same trading issue with a number of different trading partners at the same period of time. The problem is due to an unrealistic implication in both Sim's original model and our improved model, that is, it was implied that a negotiation agent has same behaviors and actions to all trading partners referring to a same trading issue. It however, is not quite true in a real world trading negotiation. In fact, when a buyer negotiates with a number of sellers regarding a same trading issue, a negotiation strategy between a buyer and a seller is kept in secret and unknown to others. To be able to reflect this fact, a revised market-driven negotiation agent model is proposed and discussed in this paper.

## 2. The revised model

Like Sim's original model and our previous improved model in [1], [2] and [3], negotiation agents in this paper also make concessions by narrowing the *spread* (difference in the proposals between negotiators). The agents concede by attempting to reduce the expected spread in the next round $t+1$ to a fraction of the actual spread in the current round $t$.

In the improved market-driven model with learning opponent eagerness, the expected spread, $k_{t+1}^{a}$, in the round $t+1$ of a buyer agent ***a*** regarding its negotiation with a seller ***b***, who is the one among all trading partners ***j***, is defined as follows:

$$k_{t+1}^{a} = [O(n_t^a, < w_t^{j \to a} >, v_t^{a \to j}), C(m_t^a, n_t^a), T(t, \tau, \varepsilon_t^{a \to b}), E(\varepsilon_t^{b \to a})] \times k_t^{a \leftrightarrow b} \quad (1)$$

where, $k_t^{a \leftrightarrow b}$ is the actual spread in the round $t$, and

- $O(n_t^a, < w_t^{j \to a} >, v_t^{a \to j})$ determines the amount of concession based on a number of trading partners, $n_t^a$, and differences in offers, $< w_t^{j \to a} >$, and bids, $v_t^{a \to j}$.
- $C(m_t^a, n_t^a)$ determines the probability that the agent ***a*** is ranked as the most preferred trading partner by at least one other agent based on the number of competitors, $m_t^a$, and trading partners, $n_t^a$.
- $T(t, \tau, \varepsilon_t^{a \to b})$ determines how much the agent should concede with respect to time according to the current round $t$, the closing round $\tau$ and the eagerness, $\varepsilon_t^{a \to b}$, from the agent ***a*** to the seller ***b***.
- $E(\varepsilon_t^{b \to a})$ determines the amounts of concession based on the learnt opponent eagerness, $\varepsilon_t^{b \to a}$, from the seller ***b*** to the agent ***a***.

Formula (1) expresses that the spread, $k_{t+1}^{a}$, which the agent ***a*** expects to achieve in the next round $t+1$, is determined as a same common spread for all trading partners ***j***. As it is the fact that the expected spreads may be different when the buyer agent, ***a***, negotiates with different trading partners. The buyer agent, ***a***, in fact makes adjustable amounts of concession to each trading partner. Moreover, the proposals or offers in a negotiation between a buyer agent and a trading partner are kept in secret and unknown to others. For example, in the case of the buyer agent, ***a***, and the two sellers, ***b1*** that has high opportunity and ***b2*** that has low opportunity, the buyer agent, ***a***, should be able to make a bid, \$100 to ***b1*** and a bid, \$200 to ***b2***.

It is obvious that the previous improved model should be further revised to meet the need in the real world trading. There is a necessity to make adjustable amounts of concession to each trading partner, respectively. Correspondingly, the proposals are not an element, $v_t^{a \to j}$, but a vector containing an enumerative elements denoted as $< v_t^{a \to j} >$. The revised model is given below.

$$< v_t^{a \to j} > = < [T(t, \tau, \varepsilon^{a \to j}), IO_t^{a \leftrightarrow j}, IO'^{a \leftrightarrow j}_t] > \quad (2)$$

Where, ***IO*** (individual opportunity) is the probability of reaching a consensus for a given proposal caused respectively by each trading partner. The details about how each function in Formula (2) is correspondingly revised or redefined are to be explained in the following sections.

## 3. Redefined competition function

Since market-driven agents are utility maximizing agents, an agent is more likely to reach a consensus if its proposal is ranked the highest by some other agent. Therefore, the amount of competition of a market-driven agent needs to be determined.

In our previous improved market-driven model, the competition function is defined as

$$C(m_t^a, n_t^a) = 1 - ((m_t^a - 1)/m_t^a)^{n_t^a} \quad (3)$$

The function, $C(m_t^a, n_t^a)$ is the probability that an agent, ***a***, is ranked as the most preferred trading partner by at least one other agent at round $t$. This function implies that

- each trading partner has a same number of competitors (the number of competitors, $m_t^a$ is the same for all trading partners),
- each seller trading partner gets a same number of demands on a trading issue, and
- each buyer trading partner gets a same number of supplies on a trading issues.

However, it is not quite true in a real world trading negotiation. A number of competitions of each trading partner may not be the same, a number of demands to a seller and a number of supplies may be different. Figure 1 shows an example of individual competition of each trading partner in a market.

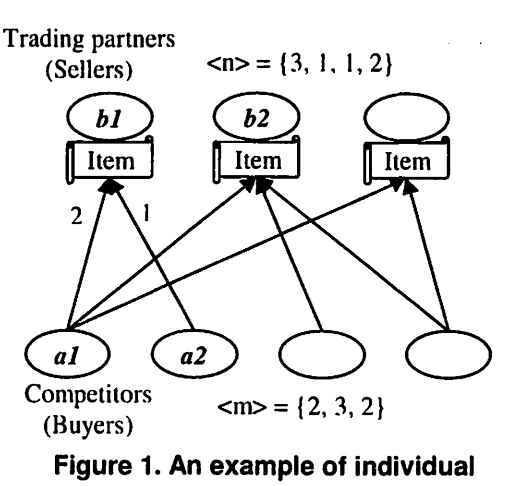


**Figure 1. An example of individual competition**

Where, as it can be seen that the buyer ***a1*** gets offers from 3 sellers and ***a2*** has only offer from only 1 seller, respectively. The seller ***b1*** receives demands from 2 buyers and ***b2*** has demands from 3 buyers, respectively. Furthermore, when the buyer ***a1*** and ***a2*** make requests of 2 and 1 items, respectively, to the seller ***b1***, ***b1*** gets 3 (= 2+1) demands in total.

To more precisely model real world trading, each individual competition of each trading partner should be able to be calculated. The competition function, thus, should be revised based on the number of supplies and demands. The individual competition function, $IC^{b\to a}$, is the probability that the buyer agent ***a*** becomes a supply target of the seller agent ***b***. If the seller gets more demands than supplies, $IC^{b\to a}$ is a smaller value. Let us denote $s^b$ as the number of items supplied by ***b***, $d^b$ as the number of items demanded to ***b***, and $i^{a\to b}$ as the number of items requested from ***a*** to ***b***. $IC^{b\to a}$ can be defined as in Formula (4) using the probability theory with combinations and permutations:

$$IC^{b\to a} = \frac{{}_{s^b}C_{i^{a\to b}}}{{}_{d^b}C_{i^{a\to b}}} \qquad (4)$$

Where, we have

- $IC^{b\to a} = 1$, when $s^b >= d^b$ because the seller ***b*** has enough supplies for its all buyers,
- $IC^{b\to a} = 0$, when $s^b < i^{a\to b}$ because it is certain that the buyer a can not be supplied all requested items, and
- $d^b >= i^{a\to b}$, because $d^b$ is the total number of requested items from all buyers, which includes $i^{a\to b}$.

Below gives two examples of calculating the individual competition in the case of Figure 1. When the seller ***b1*** has 2 supplies, the amounts of individual competition from ***b1*** to ***a1***, $IC^{b1\to a1}$, is calculated as:

$$IC^{b1\to a1} = \frac{{}_2C_2}{{}_3C_2} = \frac{(2\times 1)/2}{(3\times 2)/2} = \frac{1}{3}$$

That is to say, the probability that ***a1*** will become supplied target from ***b1*** is about 0.3. In this case, the amounts of individual competition from ***b1*** to ***a2***, $IC^{b1\to a2}$, is calculated higher like that:

$$IC^{b1\to a2} = \frac{{}_2C_1}{{}_3C_1} = \frac{2/1}{3/1} = \frac{2}{3}$$

As a result, the sum of these individual competitions becomes 1.

## 4. Redefined opportunity function

With a larger number of trading partners, an agent generally has higher probability of reaching a consensus for a given proposal. Furthermore, if there are large differences between an agent's proposal and that of its trading partners, then the chances of reaching an agreement are low. These factors are called 'trading opportunities'.

In our previous improved market-driven model, the opportunity function is defined as

$$O(n_t^a, <w_t^{j\to a}>, v_t^{a\to j}) = 1 - \prod_{j=1}^{n_t^a} \frac{v_t^{a\to j} - w_t^{j\to a}}{v_t^{a\to j} - c^a} \qquad (5)$$

The function, $O(n_t^a, <w_t^{j\to a}>, v_t^{a\to j})$ determines the amount of concession based on trading alternatives (number of trading partners) and differences in offers/bids. This function implies that a buyer agent, ***a***, has one opportunity in all negotiation. However, it is not quite true in a real world trading negotiation. The buyer ***a*** bids different prices to the sellers ***j*** (not $v_t^{a\to j}$ but $<v_t^{a\to j}>$) and there are different opportunities between them.

To more precisely model real world trading, each individual opportunity that the buyer ***a*** will obtain each utility $v_t^{a\to j}$ should be able to be calculated. The opportunity function, thus, should be revised as individual. To do that, the expression of conflict probability is considered first because it is the fundamental composition of the opportunity function. Furthermore, ***IC*** (individual competition) is taken into consideration because higher ***IC*** that means the seller has enough supplies should be make higher individual opportunity.

### 4.1 Redefined conflict probability

If a buyer ***a*** insists on its last bid and a seller ***b*** accepts it, ***a*** obtains a bid utility, $v_t^{a\to b}$, but if ***b*** does not accept it, ***a*** may be subjected to a conflict utility, $c^a$ which is the worst possible utility for ***a***. The subjective probability of ***a*** obtaining $c^a$ is called 'conflict probability'.

In our previous improved market-driven model, the maximum value of $P_{c,t}^{a\leftrightarrow b}$ (conflict probability) which is the highest probability of a conflict which the buyer agent, ***a***, may encounter in round ***t***, is given as

$$P_{c,t}^{a\leftrightarrow b} = \frac{v_t^{a\to b} - w_t^{b\to a}}{v_t^{a\to b} - c^a} \qquad (6)$$

This expression is constructed based on difference between the proposals of ***a*** and ***b***. Now, take $IC_t^{b\to a}$ (the individual competition from ***b*** to ***a*** in round ***t***) into consideration.

First, lower $IC_t^{b\to a}$ makes higher conflict probability and $IC_t^{b\to a} = 0$ makes conflict probability as 1 because the seller ***b*** does not have any supplies for the buyer ***a***. Next, $IC_t^{b\to a} = 1$ do not affect to the original expression of conflict probability (Formula 6). That is to say, $P_{c,t}^{a\leftrightarrow b}$ increases from the value of Formula (6) to 1 according as $IC_t^{b\to a}$ decreases.

Now, the conflict probability, $P_{c,t}^{a\leftrightarrow b}$ , with $IC_t^{b\to a}$ effects is redefined as

$$P_{c,t}^{a\leftrightarrow b} = 1-(1-\frac{v_t^{a\to b}-w_t^{b\to a}}{v_t^{a\to b}-c^a})\times IC_t^{b\to a} \qquad (7)$$

Let assume that the bid utility $v_t^{a\to b}$ is 0.5, the offer utility $w_t^{b\to a}$ is 0.25 and the conflict utility $c^a$ is 0.0, the followings are examples of redefined conflict probability calculation.

- The original conflict probability without $IC_t^{b\to a}$ is $(0.50-0.25)/(0.50-0.00)=0.5$.
- If $IC_t^{b\to a}=1.0$, $P_{c,t}^{a\leftrightarrow j}=1-(1-0.5)\times 1.0=0.50$
- If $IC_t^{b\to a}=0.5$, $P_{c,t}^{a\leftrightarrow j}=1-(1-0.5)\times 0.5=0.75$
- If $IC_t^{b\to a}=0.0$, $P_{c,t}^{a\leftrightarrow j}=1-(1-0.5)\times 0.0=1.00$

## 4.2 Expression of individual opportunity

This section presents the expression of individual opportunity based on $P_{c,t}^{a\leftrightarrow b}$ (redefined conflict probability) and $\varepsilon^{b\to a}$ (learnt opponent eagerness that a seller *b* has for a buyer *a* [3]). It is believed that negotiator's eagerness has strong influence on his/her decision in making proposal. With the stronger eagerness, a negotiator may make more concession to make narrow the difference between itself and others in each negotiation round, and vice versa. Therefore, an opponent eagerness will affect to individual opportunity to success a deal.

Higher $\varepsilon^{b\to a}$ makes higher individual opportunity depending on $P_{c,t}^{a\leftrightarrow b}$. On the other hand, lower $\varepsilon^{b\to a}$ makes lower individual opportunity depending on $P_{c,t}^{a\leftrightarrow b}$. Furthermore, $\varepsilon^{b\to a}$ is normally inferred as 0.5 and when $\varepsilon^{b\to a}=0.5$, individual opportunity takes the value of $(1-P_{c,t}^{a\leftrightarrow b})$ based on original opportunity function. To satisfy the demands mentioned above, the feature of an exponential function is applied. In this function, the solution is always 1 (respectively 0) when a root is 1 (respectively 0).

As a result, the probability that a buyer agent *a* will obtain a utility *v* with a seller agent *b*, namely, individual opportunity $IO_t^{a\leftrightarrow b}$ is defined as follows:

- when $(1-P_{c,t}^{a\leftrightarrow b})>0.5$

$$IO_t^{a\leftrightarrow b}=1-(1-\varepsilon^{b\to a})\wedge(\log_{0.5}[P_{c,t}^{a\leftrightarrow b}]) \qquad (8.1)$$

- when $(1-P_{c,t}^{a\leftrightarrow b})=0.5$

$$IO_t^{a\leftrightarrow b}=\varepsilon^{b\to a} \qquad (8.2)$$

- when $(1-P_{c,t}^{a\leftrightarrow b})<0.5$

$$IO_t^{a\leftrightarrow b}=\varepsilon^{b\to a}\wedge(\log_{0.5}[1-P_{c,t}^{a\leftrightarrow b}]) \qquad (8.3)$$

where, $(1-P_{c,t}^{a\leftrightarrow b})=0$ or $(1-P_{c,t}^{a\leftrightarrow b})=1$ are taken as 0.001 or 0.999 respectively because $\log_{0.5}[0]$ can not be calculated mathematically. Formula (8.1) is formed by rotating Formula (8.3) by 180 degrees around coordinates (0.5, 0.5).

Figure 2 shows examples of the individual opportunity graph when $(1-P_{c,t}^{a\leftrightarrow b})$ is nearly 0, 0.2, 0.5, 0.8 or nearly 1. If $\varepsilon^{b\to a}=0.5$, then $IO_t^{a\leftrightarrow b}$ takes the value of $(1-P_{c,t}^{a\leftrightarrow b})$, and $IO_t^{a\leftrightarrow b}$ increases from 0 to 1 depending on $\varepsilon^{b\to a}$ and $P_{c,t}^{a\leftrightarrow b}$.

In these circumstances, individual competition, conflict probability and opponent eagerness are comprehended by individual opportunity.

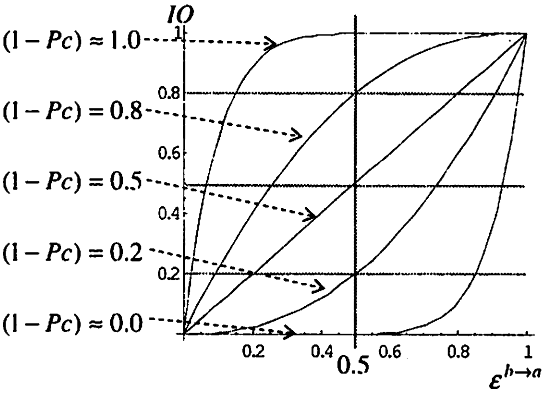


**Figure 2. Individual opportunity graph**

## 5. Negotiation strategy

This section proposes a negotiation strategy concretely for a real world trading negotiation that assumes a price negotiation is done per round. In our previous improved market-driven model, the negotiation strategy bases on a time-dependent function mainly. First, how to apply this time function for determination of the expected spread in the next round is reconsidered. Next, effects of individual opportunity to the negotiation strategy based on the time function is considered.

### 5.1. Time-dependent strategy

Deadlines put negotiators under pressure. An agent has a better bargaining position when it is very far from reaching the deadline than when the deadline is fast approaching. A negotiation strategy is classified with respect to remaining trading time.

In our previous improved market-driven model, $T(t,\tau,\varepsilon^{a\to b})$ is a time-dependent function given as

$$T(t,\tau,\varepsilon^{a\to b}) = 1-(t/\tau)\wedge(1/\varepsilon^{a\to b}) \quad (9)$$

where $t$ is current trading time, $\tau$ is the deadline, and $\varepsilon^{a\to b}$ is an eagerness from a buyer $a$ to a seller $b$. Now, when only time function is taken for the negotiation strategy, the bid utility from $a$ to $b$ in round $t$ ( $v_t^{a\to b}$ ) is determined as

$$v_t^{a\to b} = T(t,\tau,\varepsilon^{a\to b}) \quad (10)$$

where $v_t^{a\leftrightarrow b}$ takes the value from 0 to 1 that means the buyer makes amounts of concession between the reservation price and starting price.

### 5.2. Revised negotiation strategy

In this section, individual opportunity is taken to a negotiation strategy with respect to remaining trading time. Let $IO'^{a\leftrightarrow b}_t$ be the expected individual opportunity that a buyer agent, $a$, *hopes* to achieve in the current round $t$. The actual value of $IO'^{a\leftrightarrow b}_t$, which is $IO^{a\leftrightarrow b}_t$, can only be determined by the market conditions at that time. However, $IO'^{a\leftrightarrow b}_t$ can be assumed as in Formula (11) using time function:

$$IO'^{a\leftrightarrow b}_t = 1-T(t,\tau,\varepsilon^{a\to b}) \quad (11)$$

According to this function, $IO'^{a\leftrightarrow b}_t$ increases from 0 to 1 depending on $\varepsilon^{a\to b}$ per round.

If $IO^{a\leftrightarrow b}_t$ is far from (respectively near to) $IO'^{a\leftrightarrow b}_t$, then the buyer agent, $a$, will make more (respectively less) concession to reduce the spread. To bring $IO^{a\leftrightarrow b}_t$ close up to $IO'^{a\leftrightarrow b}_t$, $a$ makes an amount of concession based on following revised negotiation strategy:

- when $IO'^{a\leftrightarrow b}_t > IO^{a\leftrightarrow b}_t$

$$v_t^{a\to b} = [T(t,\tau,\varepsilon^{a\to b}) - T(t,\tau,\varepsilon^{a\to b})\times(IO'^{a\leftrightarrow b}_t - IO^{a\leftrightarrow b}_t)] \quad (12.1)$$

- when $IO'^{a\leftrightarrow b}_t < IO^{a\leftrightarrow b}_t$

$$v_t^{a\to b} = [T(t,\tau,\varepsilon^{a\to b}) - (1-T(t,\tau,\varepsilon^{a\to b}))\times(IO'^{a\leftrightarrow b}_t - IO^{a\leftrightarrow b}_t)] \quad (12.2)$$

When the actual individual opportunity is lower (respectively higher) than the expected one, the agent makes more (respectively less) concession based on time-dependent strategy to success a deal. The (12.1) and (12.2) give the details of Formula (2).

## 6. Conclusions and future work

This paper proposes a revised market-driven model for negotiation agent in a real world trading and revised negotiation strategy based on time-dependent function and individual opportunity. The individual opportunity implicitly contains the factors of individual competition, conflict probability, and opponent eagerness. These factors are revised or redefined for a real world trading that a negotiation strategy between a buyer and a seller is kept in secret and unknown to others.

It is also important to take into consideration about negotiation dependency caused that other negotiation circumstances in a certain round affect amounts of concession mutually, however, it is not taken in a revised market-driven model. Each individual opportunity for all trading partners should be implied to negotiation strategy. If the individual opportunity for one another seller is high, the buyer can make less concession with high probability to success a deal. In future work, negotiation dependency and a market implementation in the web will be discussed.

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