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Evaluations of Tactics for Automated Negotiations

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Abstract Automated negotiation under the infrastructure of e-commerce is becoming an important issue. However, although the communication protocols and frameworks of automated negotiation have been extensively investigated, the corresponding tactics and strategies are still underdeveloped and need to be evaluated further. Based on the negotiation model proposed by Faratin et al., this paper examines the performance of automated negotiation tactics and intends to provide concise suggestions for the users of automated negotiation. First, theoretical analysis is used to evaluate the behavior-dependent tactics. Constructive conclusions are obtained when single-issue negotiations are considered. Next, a new framework for applying single-issue tactics to multi-issue negotiation is proposed. Based on this framework, theoretical analysis is then extended to multi-issue cases. Finally, different from the previous work, exhaustive simulations based on two-issue negotiations are performed to evaluate the effectiveness of behavior-dependent and time-dependent tactics. The experimental results provide several important insights into negotiation tactics.

Keywords Negotiation tactics · Automated negotiation · Negotiation strategies · Software agents · e-Commerce

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1 Introduction

In the past few years, the rapid development of e-commerce is obvious to all. The footprints of e-commerce are ubiquitous and range from simple web shopping to complex virtual partnership construction through the Internet. Besides, faced with diverse user groups, different trading models have been developed in e-commerce as well, including posted-price selling, auctions and negotiations. However, if a human user is requested to monitor the trading process successively, then the convenience and efficiency of e-commerce will be greatly reduced. In view of this, automating e-commerce trading and releasing the users from continued monitoring have become important research topics.

The *software agent* technology provides a viable solution for the automation of trading in e-commerce. A software agent is a package of programs that is created on behalf of the user (trader) and is able to accomplish a delegated task autonomously (Bradshaw 1997). At present, agent technologies have been applied to several domains of e-commerce, such as shopping agents with the capability of price comparison (Maes et al. 1999) and auction agents that can bid autonomously (Wurman et al. 1998). However, when considering agent-mediated automated negotiations, there is no evidence to show a widespread adoption of such a promising framework (Lim 2003). This is not a surprise in light of the fact that negotiation is a process of resolving disputes among two or more parties and usually involves complicated strategies and tactics (Oliver 1996; Lewicki et al. 1999). Even for a well-trained negotiator, it is not uncommon to achieve breakdowns of negotiations. Thus, convincing the negotiator of adopting automated negotiation is apparently not an easy task. To remedy such an awkward situation, more elaborately-designed tactics and strategies need to be developed for automated negotiation. In particular, their effectiveness also should be clearly identified.

For the development of automated negotiation tactics, Lopes et al. (2001) classified the tactics into the five categories called *stalemate, tough, moderate, soft and compromise*, and corresponding decision functions were also proposed. However, no evaluation for those tactics is made in their work. Faratin et al. (1998) introduce a wide spectrum of negotiation decision functions to implement three families of tactics, *behavior-dependent, time-dependent, and resource-dependent,* respectively (Faratin et al. 1998). A package of hypotheses is proposed to clarify the effectiveness of these tactics and is demonstrated by a set of simulated single-issue negotiations. Following the investigations of Faratin et al., Wang and Chou (2003) provided a theoretical analysis for time-dependent tactics. They proved that, for single-issue negotiation, if both sides apply time-dependent tactics, the ratio of negotiating time to the negotiation deadline will converge to a finite constant. For the other families of tactics, simulations for single-issue negotiations are elaborated to compare the performance of a possible mixture of tactics. A more thorough investigation on the effectiveness of time-dependent tactics is also proposed by Fatima et al. (2004), and the scope is extended to multi-issue negotiations.

Although the previous work has paid attention to the evaluations of negotiation tactics, most of the theoretical analyses focus on time-dependent tactics, and simulation experiments are limited to single-issue negotiations with a random sampling of preference settings.

Based on the negotiation model proposed by Faratin et al. (1998), this paper examines the performance of automated negotiation tactics and intends to provide concise suggestions for the users of automated negotiation systems. First, a theoretical analysis is provided for behavior-dependent tactics. Useful conclusions are obtained when single-issue negotiations are considered. Next, a new framework for applying single-issue tactics to multi-issue negotiations is proposed. Based on this framework, theoretical analysis is then extended to multi-issue cases. Finally, different from the previous work, exhaustive simulations based on two-issue negotiations are performed to evaluate the effectiveness of behavior-dependent and time-dependent tactics. The experimental results show that a relatively win-win settlement could be achieved when both sides use the same tactic. And, when simultaneously considering the value, efficiency and equality of the settled contract, a simple tit-for-tat tactic would obtain better results than others.

This paper is organized as follows: Sect. 2 introduces the terminologies and assumptions used in this paper. The theoretical analysis of behavior-dependent tactics is described in Sect. 3. Applying single-issue tactics to multi-issue cases is shown in Sect. 4. Section 5 presents and discusses the experimental results. Section 6 outlines the conclusions.

2 Preliminaries

For the convenience of further discussion, the concept of the additive scoring model (Raiffa 2002), proposal tables, settlement spaces, and negotiation tactics will be introduced, respectively.

2.1 Representing the Preferences of Negotiators

In this section, the additive scoring model is introduced to present a possible way to capture the preferences of negotiators. This model has been widely adopted in various previous studies (Raiffa 2002; Faratin et al. 2002; Bui et al. 2001; Su et al. 2001; Goh et al. 2000; Cao 1982; Barbuceanu and Lo 2000).

Before further discussion, some useful terminology will be defined. In two-party multi-issue negotiations, the negotiator will provide an *offer* for each issue in each round. The collection consisting of all the offers in a certain round is referred to as a *proposal*. For each issue, the *offer zone* is the gap between the first offer and the reservation offer. In addition, to prevent an extended negotiation, the offer for each issue is usually guided by a predetermined *increment*. It is worth noting that "issues" referred to in this paper mean quantitative issues or those which can be quantified.

According to the additive scoring model (Raiffa 2002), a negotiator is possible to represent his scoring function for a proposal $p = (x_1, x_2, \ldots, x_n)$ as follow:

$$V(p) = \sum_{j=1}^{n} w_j v_j(x_j), \quad \sum_{j=1}^{n} w_j = 1, \quad w_j > 0. \tag{1}$$

In Eq. 1, $V(p)$ denotes the *value* of the proposal p for the negotiator, n is the number of issues, and w_j denotes the *weight* of issue j, which represents the relative importance of issue j to others. Also, $v_j(x_j)$ represents the *value* of offer x_j, which could be the *desirability value* or *utility value* depending on whether the risk attitude of the negotiator is considered or not (Raiffa 2002, pp. 24–32). In this paper, $v_j(x_j)$ is assumed to be in the range of [0,1], and $V(p)$ is thus restricted to [0,1] as well.

However, the additive scoring model has its limitation. As shown by Keeney and Raiffa (1976), "an additive scoring system is appropriate if and only if the value trade-offs between any two issues do not depend on the levels chosen on the remaining issues." Consequently, for cases in which the additive template cannot be applied, more fine-grained techniques, such as *hybrid conjoint analysis* (Rangaswamy and Shell 1997; Kersten and Noronha 1999), should be used to construct concrete preferences for users. It is worth noting that, although the negotiators' preferences can be captured in different ways, the theoretical analyses presented in this paper are not dependent on the construction of the $V(p)$.

2.2 Proposal Table and Settlement Space

After exploring all the options of each issue, a *proposal table* consisting of all feasible proposals can be readily generated for each negotiator. For instance, referring to the preference settings for a seller in a two-issue negotiation (shown in Table 1), his proposal table can be constructed as in Table 2 and has been sorted according to the total value for each proposal. Obviously, during negotiation, the negotiator can pick proposals from the top to the bottom to achieve a result of a higher value.

If the proposal tables for both sides have been constructed, the *settlement space* consisting of the intersection of the two proposal tables could be identified. An example settlement space is shown in Fig. 1. A particular point in the settlement space is labeled as the *Equivalent and Efficient point* (*EE-point*), which is (0.76, 0.76) in the case of Fig. 1 and is the intersection of the 45-degree line originating from (0,0) and

Table 1 An example of preference setting for a seller in a two-issue negotiation

Issue 1 (Price: US$)					Issue 2 (Warranty: years)				
w_1	u_1	max_1	min_1	Increment	w_2	u_2	max_2	min_2	Increment
0.6	Linear	100	90	10	0.4	Linear	1	3	1
#feasible offers $= (100-90)/10+1=2$					#feasible offers $= (3-1)/1+1=3$				

Table 2 The proposal table of the seller

Price (US$)	Warranty (years)	U_{Seller}
100	1	1
100	2	0.8
100	3	0.6
90	1	0.4
90	2	0.2
90	3	0

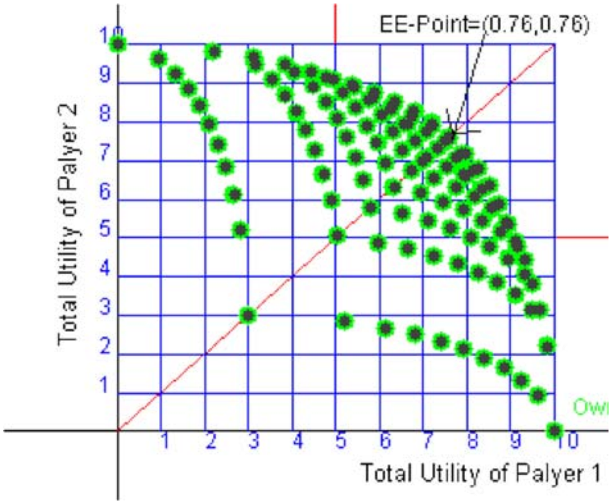

Fig. 1 A settlement space

the efficient frontier. The EE-point represents a solution simultaneously conforming to the indices of *efficiency* (located on the efficient frontier) and *equality* (both sides obtain the same value according to their own scoring functions) (Mumpower 1991; Kalai and Smorodinsky 1975).

2.3 Negotiation Tactics

According to the classification by Faratin et al. (1998), negotiation tactics based on negotiation decision functions can be divided into three families: *behavior-dependent*, *time-dependent* and *resource-dependent*. For a single-issue negotiation, the target offer of agent A at t_{l+1} for issue j is denoted as $tx_j^a(t_{l+1})$, and the actual offer $x_j^a(t_{l+1})$ can be represented by the following equation:

$$x_j^a(t_{l+1}) = \begin{cases} tx_j^a(t_{l+1}), & \text{if } \min_j^a \le tx_j^a(t_{l+1}) \le \max_j^a, \\ \max_j^a, & \text{if } \max_j^a \le tx_j^a(t_{l+1}), \\ \min_j^a, & \text{if } tx_j^a(t_{l+1}) \le \min_j^a . \end{cases} \tag{2}$$

In Eq. 2, we assume that, at t_{l+1}, agent A will accept the offer of the opponent (agent B) if the value of $tx_j^a(t_{l+1})$ is no more than that of $tx_j^b(t_l)$. Alternatively, the negotiation will break down if the time exceeds $t_{\max}^a$ or $t_{\max}^b$.

The difference of the three families of tactics can be identified by the calculation $tx_j^a(t_{l+1})$. For behavior-dependent tactics, $tx_j^a(t_{l+1})$ is heavily dependent on the offering history of the other side. For resource-dependent tactics, the calculation $tx_j^a(t_{l+1})$ does not react to the opponent's behavior but depends on the resources already spent on or left for the negotiations. Because time is a kind of resource, time-dependent tactics are obviously special cases for resource-dependent tactics.

The process of negotiation can be represented by time ticks (t_i for short) or by rounds. For a negotiation between agent A and agent B, if agent A opens first, then agent A should offer in time ticks $(t_1,\ t_3,\ t_5,\ \ldots,\ t^a_{\max})$, and agent B provides counter-offers in $(t_2,\ t_4,\ t_6,\ \ldots,\ t^b_{\max})$, where $t^a_{\max}$ and $t^b_{\max}$ denote the negotiation deadline for agent A and agent B respectively. The time ticks for the negotiation can be mapped to the concept of rounds. One round consists of two time ticks, e.g., t_1 and t_2 constitute round 1, t_3 and t_4 constitute round 2, and so on. For the convenience of discussion, rounds and time ticks are used interchangeably when describing the details of tactics in the following sections.

3 Theoretical Analysis of Behavior-dependent Negotiation Tactics

As stated earlier, evaluations of automated negotiation tactics are the cornerstone of encouraging the user to adopt automated negotiations or negotiation support systems. Thus, one of the important tactic families, behavior-dependent tactics, will be carefully examined in this section.

The core concept of behavior-dependent tactics is that the concession of the next round will depend on the history of the offers by the opponent. That is, behavior-dependent tactics treat the opponent in a *tit-for-tat* manner. In Faratin's paper, there are three such *tit-for-tat* tactics proposed, which are *Relative Tit-For-Tat*, A*veraged Tit-For-Tat*, and *Random Absolute Tit-For-Tat* (Faratin et al. 1998). In the following, the properties of the three tactics will be investigated in depth. Although the evaluations are performed on single-issue two-party negotiations, we think the results could be used as the foundation for evaluating multi-issue negotiation tactics as well.

3.1 Relative Tit-For-Tat Tactic

The Relative Tit-For-Tat tactic (RelTFT) calculates the concession of the next round by the ratio of the opponent's offers in two successive rounds. If agent A uses RelTFT, then the concession ratio for issue j at time t_{l+1}, $R^a_j(t_{l+1})$, can be obtained by Eq. 3. In particular, if δ is 1, then the ratio is determined by the last two offers of the opponent (i.e., the most recent behavior of the opponent). Thus, the target offer of the next round for agent A would be the multiplication of his last offer, $x^a_j(t_{l-1})$ and the concession ratio $R^a_j(t_{l+1})$ (see Eq. 4). For example, for a price negotiation, if the last offer of agent A (seller) is \$200, and the last two offers proposed by the opponent (buyer) are \$120 and \$140, respectively, then the next target offer of agent A would be $200 * (120/140) = 171$.

$$R^a_j(t_{l+1}) = \frac{x^b_j(t_{l-2\delta})}{x^b_j(t_{l-2\delta+2})}, \quad \text{where } \delta \geq 1,\ l > 2\delta. \tag{3}$$

$$tx^a_j(t_{l+1}) = R^a_j(t_{l+1}) \times x^a_j(t_{l-1}). \tag{4}$$

Table 3 A negotiation example in which agent A uses RelTFT ($\delta = 1$)

Agents/rounds	1	2	3	4	5	6	7	8	9
agent A (seller)	300	290*	264	242	223	207	193	181	171
agent B (buyer)	100	110	120	130	140	150	160	170	accept (180)

* Constant concession is applied at round 2 by agent A

Table 4 The offer sequence when agent A uses RelTFT ($\delta = 1$)

Rounds	1	2	3	4	...	k	...
agent A	a_1	a_2	$a_3 = a_2 * (b_1/b_2)$	$a_4 = a_2 * (b_1/b_3)$	...	$a_k = a_2 * (b_1/b_{k-1})$	...
agent B	b_1	b_2	b_3	b_4	...	b_k	...

The concept of RelTFT sounds reasonable, but we found that the concession calculated by RelTFT is in fact not that fair. Table 3 shows a negotiation example, in which agent A (seller) and agent B (buyer) dispute on the price issue. Agent A adopts RelTFT ($\delta = 1$) as the negotiation tactic, on the other hand, agent B use a simple constant concession tactic. Moreover, we assume ($\min^a$, $\max^a$) is (150, 300) and ($\min^b$, $\max^b$) is (100, 250). According to Raiffa's research (Raiffa 2002), if no exaggeration occurs in the first round, the reasonable deal price would be the average of the open offers of both sides, which is $200(= (300+100)/2)$ in this example. However, from the offering sequence in Table 3, agent A using RelTFT proposes a larger amount of concession than the opponent after round 2. In round 7, agent A's offer becomes 193, which is already lower than the reasonable price (200). If the negotiation continues to round 9, the offer of agent A is further reduced to 171, and agent B will be glad to accept such a low price. From the above example, it is observed that using RelTFT may not be beneficial to the seller, and his gain is even worse than that of the buyer who uses a simple tactic.

To further understand the characteristics of RelTFT, we continued to investigate whether a negotiator using RelTFT could obtain his expected value. First of all, the example in Table 3 is formalized as shown in Table 4, in which the offer sequences of agent A and agent B are represented by $(a_1,\ a_2,\ a_3,\ldots)$ and $(b_1,\ b_2,\ b_3,\ldots)$ according to the negotiation round. In addition, only agent A is assumed to use RelTFT. It is worth noting that, RelTFT cannot be applied in the first two rounds, therefore we use a_1 and a_2 to represent the offers in these two rounds.

In Table 4, it can be seen that the offer by agent A in round k, a_k, would be

$$a_k = a_2(b_1/b_{k-1}), \tag{5}$$

which is reduced from $a_2(b_1/b_2)(b_2/b_3)\ldots(b_{k-2}/b_{k-1})$. In fact, for any $\delta \geq 1$, if agent A proposes his offer first in each round, a_k would be

$$a_k = a_{\delta+1}(b_1/b_{k-\delta}), \quad \text{where } \delta \geq 1 \text{ and } k > \delta + 1. \tag{6}$$

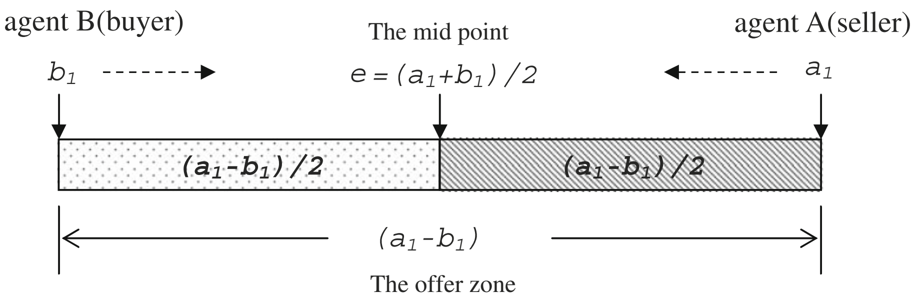

Fig. 2 The offer zone created by the negotiation setting in Theorem 1

This result shows a surprising fact: a_k only depends on b_1 and $b_{k-\delta}$ but not on $b_2, b_3, \ldots, b_{k-\delta-1}$. For the case of agent B opening his offer first, the calculation of a_k is somewhat different from that in Eq. 6, and would be

$$a_k = a_\delta(b_1/b_{k-\delta+1}), \quad \text{where } \delta \geq 1 \text{ and } k > \delta. \tag{7}$$

Based on the above discussions, we next propose two theorems to show the properties of the RelTFT tactic.

Theorem 1 *Assume that agent A and agent B conduct a price negotiation and the negotiation settings are organized as follows:*

(*a*) *agent A plays the seller and agent B plays the buyer,*
(*b*) *agent A adopts the RelTFT tactic,*
(*c*) *both sides apply the linear value function to the price issue,*

then the offer of agent A would reach the mid point, $(a_1 + b_1)/2$*, before agent B does. That is, agent B can make less accumulated concessions than* $(a_1 - b_1)/2$ *in exchange for agent A's concession to* $(a_1 + b_1)/2$.

Proof The proof is divided into the following two cases (please refer to Fig. 2 for better understanding of the proof).
Case 1 agent A (seller) propose his offer first in each round, let *e* be $(a_1 + b_1)/2$, and assume agent A propose *e* in round *k*, then we have

$$\begin{aligned} a_k &= a_{\delta+1}(b_1/b_{k-\delta}) = (a_1 + b_1)/2, \\ \text{or} \quad b_{k-\delta} &= 2a_{\delta+1}b_1/(a_1 + b_1). \end{aligned} \tag{8}$$

Based on Eq. 8, if $b_{k-\delta} < e$ is true, then the induction of the theorem can be demonstrated.

Given $a_1 \geq a_{\delta+1}$, Eq. 8 can be further rewritten as

$$b_{k-\delta} = 2a_{\delta+1}b_1/(a_1 + b_1) \leq 2a_1b_1/(a_1 + b_1).$$

Because

$$\begin{aligned}2a_1b_1/(a_1+b_1)-e &= 2a_1b_1/(a_1+b_1)-(a_1+b_1)/2\\ &= -(a_1-b_1)^2/(2(a_1+b_1))<0,\end{aligned}$$

we have $2a_1b_1/(a_1+b_1)<e$, which implies $b_{k-\delta}<e$. Thus, Theorem 1 is proven to be true in this case.
Case 2 agent B (buyer) proposes his offer first in each round.
Referring to Eq. 7, if agent A proposes e in round k, i.e., $a_k=e$, then we have

$$\begin{aligned}&a_k=a_\delta(b_1/b_{k-\delta+1})=(a_1+b_1)/2,\\ \text{or}\quad &b_{k-\delta+1}=2a_\delta b_1/(a_1+b_1).\end{aligned}\tag{9}$$

Based on Eq. 9, if $b_{k-\delta+1}<e$ is true, the theorem can be proven. Given that

$$b_{k-\delta+1}-e=2a_\delta b_1/(a_1+b_1)-(a_1+b_1)/2.$$

Because $a_\delta\le a_1$, the above equation can be rearranged as

$$b_{k-\delta+1}-e<\left(4(a_1b_1)-(a_1+b_1)^2\right)/2(a_1+b_1)<0.$$

Therefore, $b_{k-\delta+1}<e$ is true, and Theorem 1 is proven to be true in this case. □

From Theorem 1, it can be seen that the seller applying RelTFT to a price negotiation would put himself in a disadvantageous situation. However, a negotiator adopting RelTFT has an opportunity to predict when his offer will be lowered to his expectation price, say $(a_1+b_1)/2$. For the example in Table 3, if the expectation price of agent A is $(a_1+b_1)/2=(300+100)/2=200$, then he can predict he will propose \$200 in round k when b_{k-1} is \$145$(=a_2(b_1/a_k)=290*(100/200))$. That is, when the accumulated concession amount of agent B is only \$45(= \$145 − \$100), agent A would make accumulated concessions of \$100(= \$300 − \$200).

To provide a deeper insight of the RelTFT tactic, the situation of a buyer using RelTFT will be investigated in Theorem 2.

Theorem 2 *Assume that the negotiation settings are the same as those in Theorem 1, but agent A plays the buyer and agent B plays the seller, then the offer of agent A would reach the mid point, $(a_1+b_1)/2$, after agent B does if one of the following conditions is satisfied:*

(*a*) *agent A proposes his offer first in each round, and* $(a_{\delta+1}-a_1)<(a_1-b_1)^2/(4b_1)$.
(*b*) *agent B proposes his offer first in each round.*

Proof
Case 1 agent A proposes his offer first in each round.

Refer to Eq. 8, we have $b_{k-\delta} = 2a_{\delta+1}b_1/(a_1 + b_1)$. The difference between the mid-point price and $b_{k-\delta}$ is

$$(a_1 + b_1)/2 - (2a_{\delta+1}b_1/(a_1 + b_1)),$$
$$\text{or} \quad ((a_1 + b_1)^2 - 4a_{\delta+1}b_1)/(2(a_1 + b_1)).$$

If the difference is greater than zero, then we can prove that agent B would make much concession than $|a_1 - b_1|/2$ in exchange for agent A's concession to $(a_1 + b_1)/2$.

Let 'd' be agent A's concession between $a_{\delta+1}$ and a_1, i.e., $a_{\delta+1} = a_1 + d$, then the above equation becomes

$$((a_1 + b_1)^2 - 4(a_1 + d)b_1)/(2(a_1 + b_1)) > 0,$$
$$\text{or} \quad d < (a_1 - b_1)^2/(4b_1).$$

Case 2 agent B proposes his offer first in each round.

This proof is similar to the proof in Case 2 of Theorem 1. Because $b_{k-\delta+1} < e$ is true, then this case can be proven. □

We use an example to explain the application of (Case 1) in Theorem 2. For a price negotiation between agent A and agent B with an offer zone in [\$100, \$300], assume agent A plays the buyer and adopts RelTFT ($\delta = 1$), agent B plays the seller and uses an arbitrary tactic. Thus, according to conclusions of Theorem 2, if a_1 is \$100 and a_2 is less than \$133.3($= 100 + (100 - 300)^2/(4 * 300)$), agent A would not propose \$200 before agent B does. That is, if a settlement is reached in the negotiation, then the price settled on would be less than the mid-point price, \$200, and be beneficial to agent A (buyer).

3.2 Averaged Tit-For-Tat Tactic

The Averaged Tit-For-Tat tactic (AvgTFT) is similar to RelTFT, the only difference is the calculation of $R_j^a(t_{l+1})$. Equation (10) shows the $R_j^a(t_{l+1})$ of AvgTFT. For example, if agent A (seller) applies AvgTFT ($\gamma = 3$) to a price negotiation, then he will consider the offers in the previous four rounds by agent B (buyer). If the last offer of the seller is \$200 and the last four offers of the buyer are \$100, \$110, \$120 and \$130, respectively, then the next target offer of agent A, $tx_j^a(t_{l+1})$, would be \$153($=$ \$200 $* (100/130)$). It is worth noting that AvgTFT is the same as RelTFT ($\delta = 1$) when γ is 1.

$$R_j^a(t_{l+1}) = \frac{x_j^b(t_{l-2\gamma})}{x_j^b(t_l)}, \quad \text{where } \gamma \geq 1,\ l > 2\gamma. \tag{10}$$

The characteristic of AvgTFT can be further clarified by Table 5, in which the negotiation setting is the same as Table 4 except that agent A adopts AvgTFT but not RelTFT. According to Eq. 10, agent A cannot apply AvgTFT before round $\gamma + 2$, but could adopt any tactic in the first $\gamma + 1$ rounds. According to AvgTFT, agent A will

Table 5 The offer sequence when agent A adopts AvgTFT

	1	2	...	$\gamma+1$	$\gamma+2$	$\gamma+3$	...	$k-1$	k	...
agent A	a_1	a_2	...	$a_{\gamma+1}$	$a_{\gamma+1}*$ $(b_1/b_{\gamma+1})$	$a_{\gamma+1}*$ $(b_1 b_2/b_{\gamma+1}b_{\gamma+2})$	...	...	...	...
agent B	b_1	b_2	...	$b_{\gamma+1}$	$b_{\gamma+2}$	$b_{\gamma+3}$	...	b_{k-1}	b_k	...

propose $a_{\gamma+1}(b_1/b_{\gamma+1})$ in round $\gamma+2$, $a_{\gamma+1}(b_1b_2/b_{\gamma+1}b_{\gamma+2})$ in round $\gamma+3$, and so forth. Thus, the offer by agent A in round k should be

$$a_k = a_{\gamma+1}(b_1b_2\ldots b_{k-\gamma-1}/b_{\gamma+1}b_{\gamma+2}\ldots b_{k-1}), \quad k \geq \gamma+2.$$

When $k = 2(\gamma+1)$, the above equation can be rewritten as

$$a_k = a_{\gamma+1}(b_1b_2\ldots b_\gamma b_{\gamma+1}/b_{\gamma+1}b_{\gamma+2}\ldots b_{2\gamma+1}),$$
$$\text{or} \quad a_k = a_{\gamma+1}(b_1b_2\ldots b_\gamma/b_{\gamma+2}\ldots b_{2\gamma+1}).$$

In fact, when $k \geq 2(\gamma+1)$, the numerator of the second term of a_k would be fixed to $(b_1b_2\ldots b_\gamma)$. Consequently, a_k can be represented as

$$a_k = a_{\gamma+1}(b_1b_2\ldots b_\gamma/b_{k-\gamma}\ldots b_{k-1}), \quad \text{where } k \geq 2(\gamma+1),$$

$$\text{or} \quad a_k = a_{\gamma+1}(b_2\ldots b_\gamma/b_{k-\gamma}\ldots b_{k-2})(b_1/b_{k-1}), \quad k \geq 2(\gamma+1). \tag{11}$$

Based on Eq. 11, the concession amounts for RelTFT and AvgTFT are then compared, and the conclusions of Theorem 1 is tried to applied to AvgTFT. Before proceeding to Lemma 1, we first define a *successive concession* used by agent X for issue j as an offering sequence $(o_1, o_2, \ldots, o_n)$, where $u_j^x(o_1) \geq u_j^x(o_2) \geq \ldots \geq u_j^x(o_n)$ and n is the round limit.

Lemma 1 *Assume agent A and agent B conduct a price negotiation in which agent A uses RelTFT*($\delta \geq 1$) *and agent B makes a successive concession. If agent A changes his tactic to AvgTFT*($\gamma > \delta$) *before the negotiation begins, in each round k, he would make more concession than the case of using RelTFT, where* $k \geq 2(\gamma+1)$.

Proof The proof can be divided into the following four cases:
Case 1 agent A plays the seller and proposes his offer first in each round.
By applying Eq. 11, we have

$$a_{k,AvgTFT} = a_{\gamma+1}(b_2\ldots b_\gamma/b_{k-\gamma}\ldots b_{k-2})(b_1/b_{k-1}). \tag{12}$$

Alternatively, if agent A changes his mind to adopt RelTFT, a_k would be

$$a_{k,RelTFT} = a_{\delta+1}(b_1/b_{k-\delta}). \tag{13}$$

Divide (12) by (13), we have

$$a_{k,AvgTFT}/a_{k,RelTFT} = (a_{\gamma+1}/a_{\delta+1})(b_2 \ldots b_\gamma/b_{k-\gamma} \ldots b_{k-2})(b_{k-\delta}/b_{k-1}). \quad (14)$$

Because agent A is the seller and $\gamma > \delta$, $a_{\gamma+1}/a_{\delta+1}$ would be less than 1. Similarly, because agent B is the buyer and $\delta \geq 1$, $(b_2 \ldots b_\gamma/b_{k-\gamma} \ldots b_{k-2}) < 1$ and $(b_{k-\delta}/b_{k-1}) \leq 1$ are true. Therefore, $a_{k,AvgTFT}/a_{k,RelTFT} < 1$ or $a_{k,AvgTFT} < a_{k,RelTFT}$ can be concluded. That is, Lemma 1 holds for Case 1.

Case 2 agent A plays the buyer and proposes his offer first in each round.

In this case, $a_{k,AvgTFT}/a_{k,RelTFT} > 1$ should be proven. Using Eq. 14, since agent A plays the buyer, $(a_{\gamma+1}/a_{\delta+1}) > 1$, $(b_2 \ldots b_\gamma/b_{k-\gamma} \ldots b_{k-2}) > 1$, and $(b_{k-\delta}/b_{k-1}) \geq 1$ are all true, therefore $a_{k,AvgTFT} > a_{k,RelTFT}$ can be concluded.

Case 3 agent A plays the seller and agent B proposes his offer first in each round.

The proof of this case is similar to Case 1. Because agent B proposes his offer first in each round, $a_{k,AvgTFT}$ and $a_{k,RelTFT}$ would be as follow.

$$a_{k,AvgTFT} = a_\gamma(b_2 \ldots b_\gamma/b_{k-\gamma+1} \ldots b_{k-1})(b_1/b_k),$$
$$a_{k,RelTFT} = a_\delta(b_1/b_{k-\delta+1}).$$

Then, we have

$$a_{k,AvgTFT}/a_{k,RelTFT} = (a_\gamma/a_\delta)(b_2 \ldots b_\gamma/b_{k-\gamma+1} \ldots b_{k-1})(b_{k-\delta+1}/b_k). \quad (15)$$

Clearly, in this case, $(a_\gamma/a_\delta) < 1$, $(b_2 \ldots b_\gamma/b_{k-\gamma+1} \ldots b_{k-1}) < 1$ and $(b_{k-\delta+1}/b_k) \leq 1$ are all true. Thus, $a_{k,AvgTFT}/a_{k,RelTFT} < 1$ or $a_{k,AvgTFT} < a_{k,RelTFT}$ holds for this case.

Case 4 agent A plays the buyer and agent B proposes his offer first in each round.

In this case, $a_{k,AvgTFT}/a_{k,RelTFT} > 1$ needs to be proven. Using Eq. 15, since agent A plays the buyer and agent B plays the seller in this case, $(a_\gamma/a_\delta) > 1$, $(b_2 \ldots b_\gamma/b_{k-\gamma+1} \ldots b_{k-1}) > 1$ and $(b_{k-\delta+1}/b_k) \geq 1$ should be true, thus $a_{k,AvgTFT} > a_{k,RelTFT}$ holds for this case. □

Through Lemma 1, the performance of AvgTFT then can be formulated by Theorem 3.

Theorem 3 *Theorem 1 still holds true if agent A (the seller) changes his tactic from RelTFT ($\delta \geq 1$) to AvgTFT ($\gamma > \delta$) and agent B makes a successive concession in negotiation.*

Proof The proof can be obtained by directly applying Lemma 1. □

Table 6 shows a negotiation example in which agent A uses AvgTFT ($\gamma = 3$). It can be seen that agent A quickly lowers his offer after round 4. The negotiation would be settled in round 7 and agent B accepts agent A's humble offer, \$130. In comparison with the example shown in Table 3, in which agent A adopts RelTFT and the negotiation is settled at \$171 in round 9, the performance of AvgTFT is clearly inferior to that of RelTFT.

Table 6 An example of the offering sequence when agent A adopts AvgTFT ($\gamma = 3$)

Agents/rounds	1	2	3	4	5	6	7
agent A (seller)	300	290*	280*	270*	208	163	130
agent B (buyer)	100	110	120	130	140	150	accept (160)

* Constant concession is applied before round 5 by agent A

3.3 Random Absolute Tit-For-Tat Tactic

The Random Absolute Tit-For-Tat tactic (AbsTFT) computes the concession amount of the next round by adding the difference of the opponent's offers in the last two rounds to the last offer of my own side. Thus, if agent A adopts AbsTFT, then his target offer at t_{l+1} can be obtained by Eq. 16. R(M) denotes a random number between 0 and M, and s can be 0 or 1 depending on which one is more beneficial to agent A.

$$tx_j^a(t_{l+1}) = x_j^a(t_{l-1}) + (x_j^b(t_{l-2r}) - x_j^b(t_{l-2r+2})) + (-1)^s R(M), \quad \text{where } \gamma \geq 1,\ l > 2\gamma. \tag{16}$$

Among the three behavior-dependent tactics, AbsTFT seems to be the fairest one because it has the potential to make a deal near the mid-point of the *zone of agreement* (Raiffa 2002). However, such a statement is only valid for single-issue negotiations but not multi-issue cases (discussed in Sect. 4). Moreover, an exaggerated opening offer by the opponent would affect the effectiveness of all the behavior-dependent tactics, and of course, including AbsTFT.

3.4 Remarks on Time-dependent Tactics

The main difference of time-dependent tactics and behavior-dependent tactics is that time-dependent tactics completely ignore the reaction (counter offers) by the opponent and only propose offers according to a predetermined time-dependent sequence. If agent A adopts a time-dependent tactic, his offer at time t can be formulated in the following equation (Faratin et al. 1998; Wang and Chou 2003):

$$x_j^a(t) = \begin{cases} \min_j^a + \alpha_j^a(t)(\max_j^a - \min_j^a), & \text{if } u_j^a \text{ is decreasing,} \\ \min_j^a + (1 - \alpha_j^a(t))(\max_j^a - \min_j^a), & \text{if } u_j^a \text{ is increasing,} \end{cases} \tag{17}$$

where $\alpha_j^a(t)$ can be either polynomial or exponential families of functions, but only the polynomial functions are used here for simplicity (see Eq. 18).

$$\alpha_j^a(t) = \kappa_j^a + (1 - \kappa_j^a)\left(\frac{\min(t, t_{\max}^a)}{t_{\max}^a}\right)^{1/\beta}, \quad \text{where } \kappa_j^a \text{ is a constant.} \tag{18}$$

As shown in Eq. 17, the concession amount of time-dependent tactics is completely determined by $\alpha_j^a(t)$ if $\min_j^a$ and $\max_j^a$ are given. And, according to Eq. 18, $\alpha_j^a(t)$

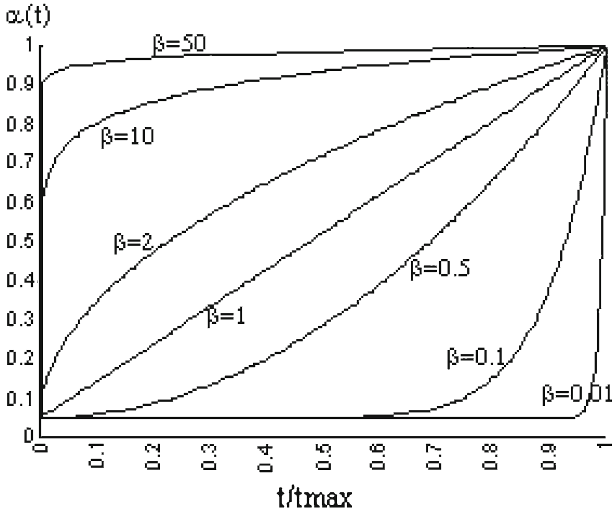

Fig. 3 The relationship between $\alpha_j^a(t)$ and β

further depends on β if $t_{\max}^a$ is constant. The relationship between $\alpha_j^a(t)$ and β is shown in Fig. 3. Apparently, the value of β determines the type of $\alpha_j^a(t)$ and therefore induces different types of tactics. If $\beta = 1$, $\alpha_j^a(t)$ will be a linear function with respect to time and thus the resultant tactic is a *Linear* tactic. In the case of $\beta < 1$, $\alpha_j^a(t)$ grows slowly at first but jumps markedly when the time is near $t_{\max}^a$ (referred as *Boulware* tactics). In contrast to Boulware tactics, if $\beta > 1$, it will result in *Conceder* tactics, which make large concessions at first but shrink the concession gradually as time passes. It is worth noting that the offer sequence of any time-dependent tactic is completely unrelated to the opponent's counter offers.

The effectiveness of time-dependent tactics has been discussed intensively in previous studies (e.g., Wang and Chou 2003; Fatima et al. 2004). Though the investigation of time-dependent tactics is not the main objective of this paper, we still propose the following comments on these tactics. Because of ignoring the opponent's reaction, applying time-dependent tactics may result in an unconditional concession even if the opponent yields nothing. On the other hand, tactics of the Boulware type are likely to enrage the opponent because no obvious concession is given until near t_{max} even if the opponent makes huge concessions. Therefore, we suggest that time-dependent tactics should be applied in combination with other families of tactics but not alone.

4 Applying Single-Issue Tactics to Multi-Issue Negotiations

In the previous sections, the performance of different tactics in single-issue negotiations was discussed. Unfortunately, the results obtained cannot be directly applied to multi-issue cases. This is mainly due to the unique nature in multi-issue negotiations, i.e., *trade-offs* among issues. In fact, it is not trivial to apply single-issue tactics to multi-issue negotiations. To tackle this problem, we first introduce two possible methods to formulate strategies in multi-issue negotiations. After that, a discussion on how to extend the theoretical result of Sect. 3 to multi-issue cases is given.

4.1 Strategies for Multi-issue Negotiations

Faratin et al. (1998) have defined a strategy for a multi-issue negotiation as the linear combination of tactics for different issues. A strategies can be composed of different tactics, which are applied to different issues. However, to further explore the trade-off feature, two possible means for applying tactics to multi-issue negotiations are proposed and described in order.

4.1.1 Offer-based Strategies

The offer-based strategies are refined from the strategy model of Faratin et al. (1998) and described as follows. Assume the target offer of agent A for issue j at time t_{l+1} is $tx_j^a(t_{l+1})$ and the actual offer $x_j^a(t_{l+1})$ is obtained by applying Eq. 3. To obtain the next proposal, different from the work of Faratin et al. (1998), we do not propose $(x_1^a(t_{l+1}), x_2^a(t_{l+1}), \ldots, x_n^a(t_{l+1}))$ directly but proceed to formulate the target value of the next proposal $TV^a(t_{l+1})$ as

$$TV^a(t_{l+1}) = \sum_{j=1}^{n} w_j^a v_j^a(x_j^a(t_{l+1})), \quad \text{where} \sum_{j=1}^{n} w_j^a = 1, \ w_j^a > 0. \tag{19}$$

Please note that the value of $TV^a(t_{l+1})$ should be restricted in [0,1].

The calculation of $TV^a(t_{l+1})$ creates the possibility to make trade-offs among issues. In fact, there is no difference for agent A to provide any proposal with the value of $TV^a(t_{l+1})$. However, these proposals of $TV^a(t_{l+1})$ may bring different meaning to the opponent. Thus, with the target value, the candidate proposals at time t_{l+1} can then be selected in the following set:

$$p^a(t_{l+1}) = \{p | p \in PT^a \wedge |V^a(p) - TV^a(t_{l+1})| \leq \lambda, \quad \lambda \in R\}. \tag{20}$$

It can be seen that, in Eq. 20, the value of each proposal in $p^a(t_{l+1})$ is not exactly equal to $TV^a(t_{l+1})$ but allows a small difference of λ with $TV^a(t_{l+1})$. This arrangement can prevent an empty $p^a(t_{l+1})$. In addition, λ can be enlarged from 0 to a predetermined boundary according to the preferences of agent A.

4.1.2 Proposal-based Strategies

The offer-based strategy has the advantage of applying different combinations of tactics to different issues, thus fully utilizing the unique feature of each tactic. However, according to offer-based strategies, the calculation of the next target offer for a certain issue would not be affected by the offers of other issues. Therefore, the trade-offs among issues are still restricted. To remedy the above problem, in multi-issue negotiation, the scope of tactics should be enlarged from distinct offers for single issues to a proposals, which is simultaneously relative to all the issues.

An example is given below to explain the concept of proposal-based strategies. Suppose agent A uses AbsTFT alone as his tactic in a multi-issue negotiation. Then the target value at time t_{l+1}, $TV^a_{AbsTFT}(t_{l+1})$, can be formulated as

$$TV^a_{AbsTFT}(t_{l+1}) = V^a(p_{l-1}) + (V^a(p_{l-2r}) - V^a(p_{l-2r+2})) + (-1)^s R(M). \quad (21)$$

The case above is referred to a *single-tactic proposal-based strategy*. When computing the next target value, not the offer for each issue but the total utilities of the last two proposals of the opponent, $V^a(p_{l-2r})$ and $V^a(p_{l-2r+2})$, are considered. That is, the tactic is applied to a proposal (a bundle of offers) and provides a better chance to explore the possible trade-offs.

The above case can be extended to a multiple-tactic negotiation. The following is an example equation used by agent A who uses both AbsTFT and Boulware to compute $TV^a(t_{l+1})$:

$$TV^a(t_{l+1}) = 0.3 \times TV^a_{AbsTFT}(t_{l+1}) + 0.7 \times TV^a_{Boulware}(t_{l+1}).$$

Based on the above discussion, the general form of $tu^a(t_{l+1})$ used by the multi-tactic proposal-based strategy can be represented as follows:

$$TV^a(t_{l+1}) = \sum_{i=1}^{m} wt_i^a TV^a_{tac_i}(t_{l+1}), \quad \text{where} \sum_{i=1}^{m} wt_i^a = 1, \ wt_i^a > 0. \quad (22)$$

In Eq. 22, m is the number of applied tactics, tac_i is the i-th tactic, and wt_i is the corresponding weight of each $TV^a_{tac_i}(t_{l+1})$. Thus, in addition to exploring the trade-off feature, the proposal-based strategy can also provide the negotiator diverse types of tactical combinations.

4.2 Theoretical Analysis for Multi-issue Negotiations

Based on the investigation in Sect. 4.1, we continue to examine the possibility of extending theoretical analyses for single-issue negotiations to multi-issues cases. To focus on the effectiveness of a specific tactic, the single-tactic proposal-based strategy is adopted for the following discussions. The analyses begin with the effectiveness of RelTFT, followed by the AvgTFT, and finally with the RndAbsTFT.

Theorem 4 *Agent A and agent B conduct a multi-issue negotiation with the negotiation settings organized as follows:*

(*a*) *agent A applies the RelTFT tactic to his single-tactic proposal-based strategy,*
(*b*) *for each proposal p in the settlement space of the negotiation,* $V^a(p) + V^b(p) = 1$.

(c) *Assume* $V^a(p^a(t_1))=1-w$, $V^a(p^b(t_1))=w$, $V^b(p^b(t_1))=1-w$, $V^b(p^a(t_1))=w$, *where* $0 < w < 1$ *and* $p^a(t_1)$ *and* $p^b(t_1)$ *are the first proposals of agent A and B respectively.*

then, according to their own value functions, agent B can make smaller accumulated value concessions than 0.5 in exchange for agent A's concession to the value of 0.5.

Proof Similar to Theorem 1, the proof is divided into the following two cases.
Case 1 agent A proposes his offer first in each round. Assume agent A's proposal value is 0.5 in round k, then we have

$$V^a(p^a(t_k)) = V^a(p^a(t_{\delta+1}))(V^a(p^b(t_1)/V^a(p^b(t_{k-\delta})) = 1/2, \text{ or}$$
$$V^a(p^b(t_{k-\delta})) = 2wV^a(p^a(t_{\delta+1}))$$

Given $V^a(p^a(t_1)) \geq V^a(p^a(t_{\delta+1}))$, the above equation can be rewritten as

$$V^a(p^b(t_{k-\delta})) \leq 2w(1-w).$$

Because,

$$2w(1-w) - 1/2 = -(2w-1)^2/2 \leq 0 \quad \Rightarrow \quad 2w(1-w) \leq 1/2$$

We have:

$$\begin{aligned} & V^a(p^b(t_{k-\delta})) \leq 1/2 \Leftrightarrow 1 - V^b(p^b(t_{k-\delta})) \leq 1/2 \\ \Leftrightarrow \ & (1-w) - V^b(p^b(t_{k-\delta})) \leq 1/2 - w \\ \Leftrightarrow \ & V^b(p^b(t_1)) - V^b(p^b(t_{k-\delta})) \leq 1/2 - w \end{aligned}$$

Because the right-hand side of the above equation is exactly the accumulated concession value of agent B, Theorem 4 is proven to be true in this case.
Case 2 agent B proposes his offer first in each round. Assume agent A's proposal value is 0.5 in round k, then we have

$$\begin{aligned} & V^a(p^a(t_k)) = V^a(p^a(t_\delta))(V^a(p^b(t_1)/V^a(p^b(t_{k-\delta+1}))) = 1/2, \\ & \text{or } V^a(p^b(t_{k-\delta+1})) = 2wV^a(p^a(t_\delta)) \end{aligned}$$

The succeeding proof is analogous with Case 1 and is omitted for simplicity. Finally, we also have:

$$V^b(p^b(t_1)) - V^b(p^b(t_{k-\delta+1})) \leq 1/2 - w$$

That is, the accumulated concession value of agent B is less than 1/2, and Theorem 4 is also proven to be true in this case. □

It can be seen from Theorem 4 that using RelTFT along in multi-issue negotiations would put the negotiator in an unfavorable situation. By applying the AvgTFT tactic to the single-tactic proposal-based strategy, similar conclusions such as Theorem 3 can be obtained by demonstrating that the concession amount of AvgTFT in each round would exceed that of RelTFT.

In applying AbsTFT to multi-issue negotiations, a different outcome was observed from that in single-issue cases and is described as follows. Assume agent A and agent B conduct a multi-issue negotiation, and the last two proposals of agent B are $p^b(t_{k-1})$ and $p^b(t_k)$. According to AbsTFT, agent A should make a value concession of an amount preferably equal to $D^a = V^a(p^b(t_k)) - V^a(p^b(t_{k-1}))$. However, because both sides have different value functions, agent B's concession, $D^b = V^b(p^b(t_k)) - V^b(p^b(t_{k-1}))$, may be less (or greater) than D^a and result in a non-reciprocal situation. That is, the effect of applying AbsTFT to multi-issue negotiations is not as definite as that in single-issue cases. Even so, applying AbsTFT is not harmful to the negotiations. Instead, such an uncertainty brings new opportunities to both sides of the negotiation, which can help make the strongly distributed nature (zero-sum) of AbsTFT become more integrative (win–win). For example, in the above case, agent B can carefully pick the next proposal from the settlement space and try to make a small concession (D^b) in exchange for a large return (D^a). Similarly, agent A can do as agent B does. As a result, a relatively win–win settlement could possibly be obtained in such a mutual exploration by both agents.

5 Simulation Experiments

In this section, to evaluate the effectiveness of different tactics for multi-issue negotiations, extensive simulation experiments are performed. And, the statistics of experimental results are then presented to provide helpful suggestions for negotiators.

5.1 Experiment Setting

5.1.1 Generation of Negotiation Cases

To provide an objective view of evaluations, we designed a pseudo-exhaustive simulation for two-issue negotiations based on the additive scoring model. In addition, some restrictions have also been introduced to limit the complexity of the simulation. First, the increment of weight for each issue is set at 0.1. Consequently, there could be C(9,1) possible weight combinations for the two issues, and thus $81 (= \text{C}(9, 1) * \text{C}(9, 1))$ combinations in total for a two-party negotiation. Next, for the value function of each issue, a limited type of function forms are allowed in the simulation, which are: linear-increasing, linear-decreasing, convex-increasing, convex-decreasing, concave-increasing and concave-decreasing (Mumpower 1991). Therefore, there would be $324 (= (6 * 6) * (3 * 3))$ possible combinations of value functions for a two-party negotiation if the opponent always has an opposite interest for each issue. As a result, $26,244 (= 81 * 324)$ negotiation cases can be generated by the above arrangement. Please refer to Table 7 for a better understanding. A similar enumeration for three-issue negotiations would obtain up to $7,558,272 (= \text{C}(9, 2) * \text{C}(9, 2) * (6*6*6) * (3*3*3))$ cases. Thus, only two-issue negotiations are considered here for sake of efficiency.

Table 7 Preference settings of two-issue negotiations for a negotiator

Parameters	Assumptions	Possible combinations
w_1, w_2	Assume the range of w_i is from 0.1 to 0.9, and 0.1 is the smallest increment.	$81 = \mathrm{C}(9, 1) * \mathrm{C}(9, 1)$
u_1, u_2	Only six typical function forms are allowable, and assume the two sides have opposite interests for each issue.	$324 = (6 * 6) * (3 * 3)$

Table 8 Parameters of negotiation tactics

Tactic group		Parameters
Behavior-dependent	RelTFT (Relative Tit-for-Tat)	$\delta = 1$
	AvgTFT (Averaged Tit-for-Tat)	$\gamma = 4$
	AbsTFT (Random Absolute Tit-for-Tat)	$\gamma = 1$, $\mathrm{M} \in [0, 5]$
Time-dependent	Boulware	$\beta = 0.2$
	Linear	$\beta = 1$
	Conceder	$\beta = 2$

5.1.2 Parameter Settings of Negotiation Tactics

In the experiment, to clearly demonstrate the effectiveness of each tactic, single-tactic proposal-based simulations were performed. Table 8 shows the parameter settings for each tactic. The offer zone for each issue for both side is set in [0,100], in which the increment of each offer is 5. As described in Sect. 2, agent A will accept the proposal of agent B, p_n, if $U^a(p_n) > U^a(p_{n+1})$, where p_{n+1} is the next target proposal of agent A, and vice versa. The limit of negotiation rounds is set to be 200.

5.1.3 Evaluation Indices

The following three indices are used to evaluate and compare the effectiveness of these tactics.

(a) *Settled utilities* (for both sides): this is the most common index to show whether or not a tactic brings benefits to a negotiator. As shown in Sect. 2, the total utilities of the settled proposal p can be obtained by $U^a(p)$ and $U^b(p)$.
(b) *Distance to EE-point*: the distance between the settled point and the EE-point in the settlement space can be used to evaluate whether the settlement is efficient and fair or not. The smaller the distance to the EE-point is, the more efficient and fairer the settlement is.

(c) *Rounds to reach an agreement*: A lengthy negotiation incurs penalties for resource consumption, thus shrinking the utilities obtained by the negotiators indirectly.

5.2 Experimental Results

This section presents the experimental results based on the setting described in 5.1. The evaluations of each tactic according to the three feature indices are also provided.

5.2.1 Settled Utilities

Table 9 presents the averaged settled utilities for both sides (agent A and agent B). Note that, only settled cases are considered here. The first column in Table 9 shows the tactics employed by agent A and the first row shows those used by agent B. In negotiation, agent A always proposes his offers before agent B in each round. The results shown in each cell of Table 9 are generated by averaging the settled utilities of all 26,244 negotiation cases corresponding to a certain tactic pair. For all, up to $944, 784 (= 36 * 26{,}244)$ negotiation cases are simulated in this experiment. Besides, to obtain a macro-scope of the effectiveness for each tactic, these averaged settled utilities are also averaged again for each tactic and are shown in the last column: Avg. (Rank). The implications of these results are discussed below.

(1) A relatively win-win result could be obtained when both sides use the same tactic. Referring to the diagonal cells of Table 9, we find that high utilities are simultaneously achieved by agent A and agent B. Besides, the differences of both sides in these cases are smaller than those of using different tactics. Especially, when considering the AbsTFT–AbsTFT pair, a significantly mutually beneficial result is obtained (0.633/0.631). Thus, an important conclusion can be formulated as follows. Without revealing the preferences of both sides, it is proper to suggest both sides adopt the same tactic for the win–win purpose.
(2) AbsTFT is the best one of the behavior-dependent tactics. Among the three behavior-dependent tactics, the ranking order is AbsTFT (2), RelTFT (4) and AvgTFT (6). This result matches the conclusions of Sect. 3 for single-issue negotiations, and demonstrates the excess concessions generated by RelTFT and AvgTFT are unfavorable to the negotiator. In fact, the performances of RelTFT and AvgTFT are even worse than that of the simple Linear tactic.
(3) Boulware achieves the best performance of all the six tactics, but AbsTFT provides the most promising results. It is not a surprise that, because of its delayed concession feature, Boulware obtains high utilities in the Boulware/Linear and Boulware/Conceder pair. However, we can find that Boulware loses its advantage when competing with AbsTFT (the result is 0.482/0.738). Besides, the AbsTFT obtains better utilities consistently than the opponent adopting any other tactics. Thus, of the six tactics, AbsTFT is the most promising tactic. (In fact, there is no need to show the friendship first to a pure time-dependent tactician.)

Table 9 The settled values for both sides according to the tactic pairs used

Tactic pairs (settled values)		agent B						Avg. (Rank)
		RelTFT	AvgTFT	AbsTFT	Conceder	Linear	Boulware	
agent A	RelTFT	**0.599/0.597***	0.61/0.533	0.576/0.635	0.596/0.619	0.574/0.64	0.574/0.637	0.589/0.610 (4)
	AvgTFT	0.527/0.617	**0.557/0.559**	0.505/0.654	0.486/0.701	0.401/0.769	0.384/0.776	0.477/0.679 (6)
	AbsTFT	0.638/0.576	0.651/0.511	**0.633/0.631**	0.718/0.504	0.706/0.52	0.727/0.498	**0.679/0.540 (2)**
	Conceder	0.602/0.61	0.683/0.506	0.502/0.715	**0.613/0.617**	0.498/0.725	0.243/0.888	0.524/0.677 (5)
	Linear	0.634/0.579	0.768/0.404	0.509/0.714	0.724/0.498	**0.619/0.621**	0.337/0.829	0.599/0.608 (3)
	Boulware	0.627/0.58	0.78/0.377	0.482/0.738	0.887/0.245	0.827/0.34	**0.613/0.619**	**0.703/0.483 (1)**

* Where 0.599 is the average settled utilities of agent A, and 0.597 is that of agent B

Table 10 The averaged distance to the EE-point of each tactic-pair

Tactic pairs (Dist. to EE)		agent B						Avg.
		RelTFT	AvgTFT	AbsTFT	Conceder	Linear	Boulware	
agent A	RelTFT	**0.185**	0.206	0.183	0.221	0.254	0.233	0.214
	AvgTFT	0.206	**0.213**	0.21	0.228	0.334	0.328	0.253
	AbsTFT	0.184	0.207	**0.176**	0.271	0.273	0.281	**0.232**
	Conceder	0.205	0.211	0.262	**0.125**	0.191	0.485	0.247
	Linear	0.242	0.327	0.277	0.189	**0.118**	0.373	0.254
	Boulware	0.227	0.335	0.294	0.481	0.368	**0.127**	**0.305**

5.2.2 Distance to EE-point

As described in Sect. 2, a settled point near the EE-point implies the deal conforms to the principles of being fair and efficient (Pareto-optimal). The average distances to the EE-point of each tactic-pair negotiation are listed in Table 10. And, the averages of the averaged distance are shown in the last column (Avg.). The discussion of the results is given below.

(1) If both sides use the same tactic, the averaged distances are relatively small. Again, refer to the diagonal cell of Table 10, the averaged distances in these cases range from 0.125 to 0.213 and are relatively smaller than those of the other tactic-pair. This result encourages us again to suggest both sides use the same tactic in negotiation.
(2) On average, Boulware incurs the largest distance to the EE-point (0.305). This implies that, although applying Boulware obtains high rewards (as shown in Table 9), it is quite possible to cause an unfair and inefficient settlement. Thus, a negotiator using Boulware alone could make a negative impression (e.g., greedy, non-reciprocal) on his opponent. On the contrary, the averaged distance to the EE-point of the AbsTFT tactic is 0.232 and significantly smaller than that of Boulware. In conclusion, AbsTFT is still superior to Boulware according to the index of distance to the EE-point.

5.2.3 Rounds to Reach an Agreement

The rounds (time) required to reach an agreement are related to the resource consumption in the negotiation. To realize the time penalty incurred by each tactic, the average rounds to reach an agreement for each tactic-pair are shown in Table 11. Note that only the settled cases are considered in the table.

(1) On average, behavior-dependent tactics cause less negotiation rounds than time-dependent tactics do. Especially, the RelTFT and AvgTFT lead early settlements which need 54 and 42 rounds on average. Clearly, this is caused by the excess concessions generated by these two tactics.
(2) The Boulware tactic causes lengthy negotiations (151 rounds on average) and thus incurs a large amount of time consumption, which is not surprising because

Table 11 The average rounds to reach an agreement of each tactic-pair

Tactic pairs (Avg Round)		agent B						Avg. (Rank)
		RelTFT	AvgTFT	AbsTFT	Conceder	Linear	Boulware	
agent A	RelTFT	15	11	25	41	74	159	54 (5)
	AvgTFT	10	9	20	22	47	144	42 (6)
	AbsTFT	24	21	28	67	99	171	68 (3)
	Conceder	42	24	65	33	56	128	58 (4)
	Linear	75	47	100	56	78	139	82 (2)
	Boulware	160	143	171	127	139	166	151 (1)

Table 12 The statistics of settlement ratio for each tactic-pair

Tactic pairs (settlement ratio)		agent B					
		RelTFT	AvgTFT	AbsTFT	Conceder	Linear	Boulware
agent A	RelTFT	0.766	0.93	0.762	1	1	1
	AvgTFT	0.932	0.999	0.932	1	1	1
	AbsTFT	0.754	0.931	0.584	1	0.999	1
	Conceder	1	1	1	1	1	1
	Linear	1	1	1	1	1	1
	Boulware	1	1	1	1	1	1

of its delayed concession feature. However, suppose the round limit is shortened from 200 to 130, there would be few deals made by using Boulware in these negotiations. These results demonstrate the comments shown in Sect. 3.4.

The above two statements imply that, if time is critical to the negotiator and reasonableness is also required in negotiations, behavior-dependent tactics would be the better choices than time-dependent tactics.

5.2.4 Settlement Ratio

All the above statistics with respect to different tactic-pairs are based on settled cases. However, if the ratio of settlement for a certain tactic is relatively low, its effectiveness will be negatively affected no matter how well it behaves in these settled cases. To provide more insight into the effectiveness of different tactics, the ratio of settlement for each tactic-pair is given in Table 12. It can be seen that the settlement ratio of behavior-dependent tactic-pairs (the upper-left corner of this table) is relatively lower than those of other pairs. The results show that, if both sides simultaneously behave in a tit-for-tat manner, the possibility of settlement would be decreased and especially in cases where the AbsTFT–AbsTFT pair is used, which resulted in the lowest ratio of 0.584. One possible reason for the above observation is that, in negotiation, sincere concessions may not be appreciated by the opponent and may result in an indifferent return (because his value function is different from yours). Then, a misunderstanding may occur and mutual revenge may be taken by both sides according to the "reciprocal" principle. Obviously, such a destructive procedure will lead to a breakdown in negotiations.

6 Conclusions

This paper presented theoretical analyses for evaluating the effectiveness of behavior-dependent tactics; first considering single-issue negotiations and then extending those results to multi-issue cases. A framework for applying single-issue tactics to multi-issue negotiations was also proposed as the basis for analysis. After that, extensive simulation experiments were performed to examine the effectiveness of three tactic families. The main results achieved by our work included: (i) showing that RelTFT and AvgTFT did not act in a tit-for-tat manner, causing the negotiator to pay more in exchange for less return; furthermore, AvgTFT behaved even more poorly than RelTFT; (ii) if both sides used the same tactic, a relatively win-win settlement could be obtained; (iii) depending on the value, efficiency, and equality of the settled contract, the simple tit-for-tat tactic, AbsTFT, obtained better results than the others.

The application of our work is manifold and may include the following: First, after understanding the effectiveness of each tactic, the negotiator can formulate a proper strategy to fulfill his predetermined objective more accurately. Second, in a semi- or fully-automated negotiation environment, these evaluations would make the negotiator (at least partially) more comfortable to delegate his role to software agents, which would be helpful to further bring negotiations into the territory of e-Commerce. Finally, when third-party intervention is allowed in negotiations, the mediator can provide constructive suggestions for each negotiator according to the results obtained in this work.

To popularize semi-/fully-automatic negotiations in e-Commerce, in addition to elaborating evaluations for existing tactics as in this paper, some diverse thinking can be further considered. First, new tactics for multi-issue negotiations, which intrinsically consider the trade-off nature of this type of negotiations, should be developed. Borrowing tactics from single-issue negotiations, such as price haggling, is not always profitable for multi-issue cases. Next, as discussed in Sect. 5, misunderstandings could occur often because both sides have different value functions. To remove the ultimate causes of trouble, we think developing techniques for predicting the opponent's preferences are definitely required. Through the results of prediction, a negotiator is more likely to make an "effective concession", which is actually beneficial to his opponent. Certainly, a suitable preference model will be necessary for a successful prediction. Besides the above considerations, as stated earlier, negotiators more easily accept a well-simulated negotiation tactic or strategy before it is put to practical use. Thus, developing more complete and efficient simulation techniques is also critical. For this purpose, the genetic algorithm could be a good candidate to take both completeness and efficiency into account simultaneously.

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