Cognitive Fuzzy-Based Behavioral Learning System for Augmenting the Automated Multi-Issue Negotiation in the E-Commerce Applications

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Abstract

Evolution of agent-based technology presents behavioral learning and sustainable negotiation challenges in e-commerce applications. In particular, the challenge of designing the negotiation strategy to incorporate sustainability in e-commerce business that can leverage the agent to reach its objectives by increasing the negotiation coordination and cooperation with the opponent agents. Therefore, the proposed research introduces the negotiation strategy sustainable solution using a cognitive fuzzy-based behavioral learning system which can change the preferences of negotiating agents according to human psychological characteristics. It will mimic the attitudes of human risk, patience and regret during the course of bilateral negotiation and also change the preference structures according to the fuzzy logic rules. As a result, the proposed negotiation strategy makes significant improvements on various parameters such as utility value, success rate, total negotiation time, and communication overhead while changing the negotiation rounds from 50 to 500. Since this system leverages the negotiation strategy of the agent by taking appropriate decisions to reach better agreement based on the interest, belief and psychological characteristics of negotiating opponents. Moreover, the usage of negotiation in the cloud-based platform can leverage the e-commerce applications to handle as many requests as possible due to its dynamic elasticity.

Keywords: Multi-agent system, Negotiation system, Cognitive learning, Fuzzy-based behavioral learning, E-commerce application

1 Introduction

Cloud computing has become an essential part of emerging information technology business owing to its on-demand self-service provisioning and metering facilities. Moreover, it offers high level services availability, and throughput after confirming the Service Level Agreement (SLA) between the consumers and service providers. In some cases, providers are not able to provision the cloud services with fully customized quality of service parameters as required by the consumers owing to its predefined SLA template-based provisioning mechanism [1]. This key limitation leads to following challenges: (a) maximization of service providers revenue and provide differentiated SLA-based cloud management system that can satisfy various levels of consumers; (b) customer-driven cloud service provisioning that can provide personalized service access according to the negotiation capability; and (3) enhanced broker-based negotiation strategy that can improve coordination and communication among the negotiation participants. To overcome the above challenges, proposed research study focused on developing the agent-based intelligent negotiation framework with cognitive fuzzy-based behavioral learning negotiation strategy. It can enforce the negotiable SLA concept in the cloud management system and also improves coordination among the negotiating parties by reaching maximum consensus. As a result, the proposed approach can maximize the utility value and success rate among the negotiating parties.

The negotiation strategy's major objective is to improve the mutually acceptable agreement (consensus) among the negotiating participants where they have cooperative or non-cooperative behavior with conflicting or similar negotiation interests. Agent-based technology is embedded in the real-time manufacturing scheduling to automate the negotiation process by generating offers or counteroffers with appropriate concessions and constraints. Usually, the interactions are realized concerning several negotiation attributes such as price, delivery time, and quality of service under different weight parameters to maximize the participants' utility value and sustainable outcomes (service provider and consumer) [2]. Nowadays, a complex form of multi-attribute-based negotiation involves more challenges in predicting opponents' behavior and making appropriate decisions on generating offers based on utility estimation [3]. More complex and time-consuming multilateral negotiation was introduced to dramatically improve the number of negotiation consensus among the participants. It makes the predictive decision making in the agent's negotiation strategy using fuzzy inference logic for maximizing their utility value [4].

The existing concurrent negotiation strategy can significantly improve utility parameters due to the weighted combination of market environments like opponents' concession rate and response time [5]. To increase the success rate among the negotiating parties, a three-phase automated negotiation system is developed to fulfill the requirement of composite service [6]. To improve both success rate and utility value among the negotiating participants, a more trending fuzzy negotiation strategy selection system was developed to select the appropriate negotiation strategy from the bunch of strategies according to the cloud trading market [7]. Similarly, an adaptive trade-off strategy is used in multi-objective contexts such as utility value, success rate, and resource management [8]. All the above trending negotiation strategies are mostly time-dependent and can provide only a fixed concession rate during the negotiation process. The novel strategy was developed using adaptive concession rate by choosing the negotiation attribute based on opponent concession patterns. This strategy can achieve high utility value but not guarantee the success rate among the participants. Therefore, the cognitive fuzzy-based behavioral learning negotiation strategy is proposed to achieve sustainable development by focusing on both utility value and success rate improvement.

The proposed research study involves the sequence of contributions such as: (a) the design and development of agent-based automated negotiation framework for enhancing cloud-based e-commerce service application, (b) formulation of negotiation process, and (c) the development of cognitive fuzzy-based behavioral learning negotiation strategy for improving the utility value and success rate among the negotiating parties.

2 Related Works

Negotiation strategies about agent-based e-commerce negotiation framework in the cloud environment can be classified as shown in Figure 1. It gives the taxonomy of negotiation strategy in the trade-off, dynamic, learning, concession, dependency, constraint, and hybrid behaviors. The static trade-off strategy generates the sequence of negotiation proposals or offers with the same aggregated utility value by differing the attributes like price, time-slot, and QoS parameters [9]. In the case of adaptive and similarity-based trade-off strategy, adaptive opponents based on expected utility are chosen and enhance the trade-off through a fuzzy-based similarity concept [10]. To avoid the uncertainty of outcomes in existing negotiation strategies, an automatic semantic reconciliation strategy is followed by real-time analysis and identification factors. To improve the cooperation among the negotiating parties, the strategy like linear, conciliatory and conservative concession is used to provide a sequence of a linear concession during the entire negotiation stage, large concession in an earlier stage and a smaller concession at a later stage, and smaller concession at a previous stage and large concession at later stage respectively [11].

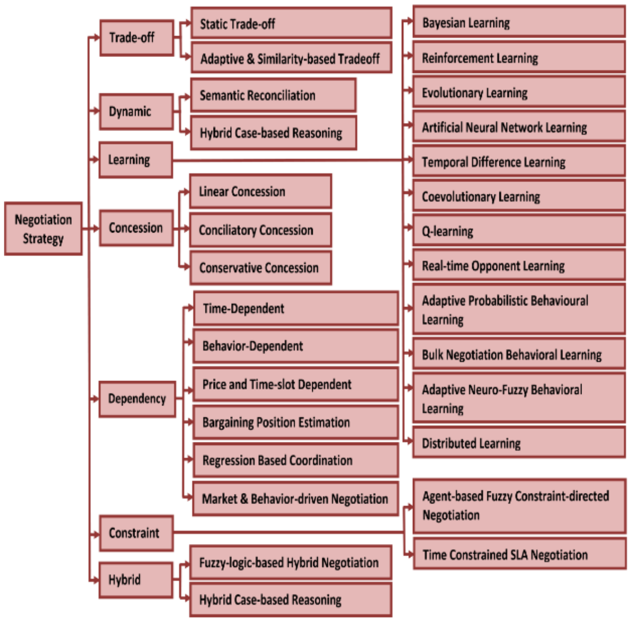

Figure 1. Taxonomy of negotiation strategy

Apart from other negotiation strategies, some new strategies will generate the negotiation offer at each stage depending on the concern behavioral approaches like time & behavior [12], price-time-slot, bargaining position estimation, regression-based coordination [13], and market-behavior-driven [14]. Sometimes, constraints are enforced in the negotiation strategy to generate offers about variable constraints strictly. Despite using learning and dependency-based strategy, a time-constrained service level agreement is focused on devising the decisions in the bargaining model without any computational complexity [15]. To satisfy the negotiating participant according to the expected quality of service attributes, a novel agent-based fuzzy constraint-directed strategy was enforced to guarantee the participants' quality of service preferences. This strategy integrates the time, behavior, and market factors to make imprecise attribute preference using fuzzy membership function, which provides better coordination among the participants [16].

To overcome the break-offs, effective behavioral learning strategies like Bayesian, reinforcement, evolutionary, artificial neural network [17], temporal difference [18], co-evolutionary [19], Q-learning [20], real-time opponent [21], adaptive probabilistic behavior [22], bulk negotiation behavior [23], adaptive neuro-fuzzy behavior [24] and distributed learning approaches are enforced during negotiation decision making process. These behavioral learning strategies could significantly improve the negotiation break-offs but increase the complexity of the system. It can be easily overcome through some hybrid negotiation strategies, hybrid case-based reasoning, and fuzzy-logic-based hybrid negotiation approaches [25] [26]. All the above strategies may be restricted to some vague constraints and preferences, leading to negotiation agreement among the participants having a common interest. According to these literature studies, following research issues are identified such as generating negotiation offers, fixing concession rate, and learning opponent behaviors. Therefore, the proposed research focused on developing fuzzy-based behavioral learning negotiation strategy that can overcome the pitfalls of existing approaches [27].

3 Proposed Agent-based Intelligent Negotiation Framework

The architecture of an agent-based intelligent cloud service negotiation framework is proposed in Figure 2 for enhancing the e-commerce negotiation among the participants. It consists of a combination of automated agents such as service consumer agents (SCAs), service provider agents (SPAs), and intelligent third-party broker agents (ITBAs). These agents will coordinate with automated services such as directory facilitator (DF) registry, jade gateway agent, universal description, discovery, and integration (UDDI) registry. Usually, all the available SPA will initially publish the list of cloud services in the UDDI registry they wish to sell in the negotiation market. Then, these services published in the registry shall not be accessible directly by the automated agents. Therefore, the intermediate jade gateway agent service is exploited to interpret the UDDI registry services to the DF registry automatically. The jade gateway agent will periodically update all the service details provided by various service providers in the DF registry. This update will happen without any third-party intervention of broker or any other agents. As a result, all the SCA can automatically search the required services in the DF registry and directly bind to the appropriate SPA for further negotiation process. Here, the SCAs will generate their corresponding service consumers' negotiation preferences and communicate the same to ITBA which in turn negotiate with a set of SPAs. At each ITBA, the number of agents interaction increases depending on the number of SPAs available during the negotiation process. All these agents' interaction will be effectively managed by the negotiation framework itself. Moreover, an agent controller component is available in the negotiation framework to support all kind of coordination and communication among the agents involved in the negotiation process. Next, the SPAs will generate the negotiation preferences of the corresponding service provider. The actual negotiation process will be carried out between the ITBAs and SPAs. During negotiation, the sequence of negotiation offers and counteroffers are exchanged between the negotiating parties by varying the preferences of the negotiation service attributes. The amount of concession and trade-off decisions against the negotiation attributes will be carried out at each negotiation round through the corresponding negotiation strategy adapted at the negotiating end. The negotiation strategy makes the appropriate decision to increase or decrease negotiation attributes' preferences, which may increase or decrease the parties' utility value. In this research, a cognitive fuzzy-based behavioral learning negotiation strategy is proposed to be exploited in the ITBAs to maximize the service consumer's utility value and success rate. Increasing the number of negotiating agents will improve the performance of negotiation framework by minimizing the total negotiation and increase the overhead in the broker part which is not an issue due to elasticity of cloud-based broker resource.

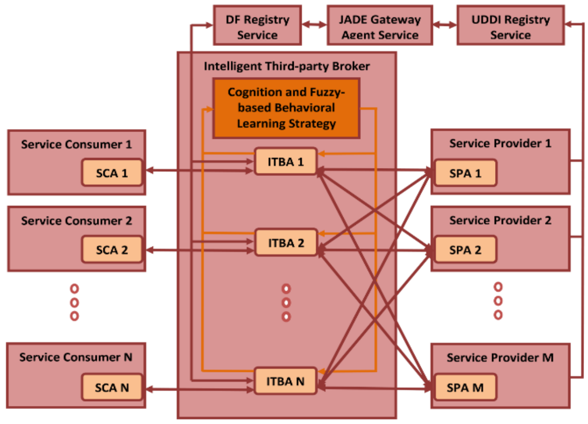

Figure 2. Architecture of Agent-based Intelligent Negotiation Framework

3.1 Formulation of negotiation process

The sequence of negotiation processes between the set of $ITBAs = \{ITBA_1, ITBA_2, \dots, ITBA_n\}$ and $SPAs = \{SPA_1, SPA_2, \dots, SPA_m\}$ can be formulated by the set of offers or counteroffers $\rho^\tau = \{\rho_O^{\tau_1}, \rho_{CO}^{\tau_2}, \rho_O^{\tau_3}, \rho_{CO}^{\tau_4}, \dots, \rho_O^{\tau_{k-1}}, \rho_{CO}^{\tau_k}\}$ exchanged concerning period τ. Here, the set $\rho^\tau = \{\rho_O^{\tau_1}, \rho_O^{\tau_3}, \dots, \rho_O^{\tau_{k-1}}\}$ denotes the sequence of offers generated by the $ITBAs$ and the set $\rho^\tau = \{\rho_{CO}^{\tau_2}, \rho_{CO}^{\tau_4}, \dots, \rho_{CO}^{\tau_k}\}$ denotes the sequence of counteroffers received by the $ITBAs$ from the respective $SPAs$. Each negotiation offer $\rho_O^{\tau_1}$ is generated by varying the preferences of n number of negotiation attributes $\rho_O^{\tau_1} = \{\rho_O^{x_1 \leftarrow [0,1]}, \rho_O^{x_2 \leftarrow [0,1]}, \dots, \rho_O^{x_n \leftarrow [0,1]}\}$. After receiving the counteroffer from the $SPAs$, the broker agents can respond to the opponent's based on the decision-making function employed in the proposed negotiation strategy, as shown in equation (1).

$$Response\ \rho_{CO}^{\tau_2}(f_D) = \{Accept(\rho_{CO}^{\tau_2}),\ if\ U_{ITBA}(\rho_{CO}^{\tau_2}) \geq U_{SPA}(\rho_{CO}^{\tau_2})\ Reject(\rho_{CO}^{\tau_2}),\ if\ U_{ITBA}(\rho_{CO}^{\tau_2}) < U_{SPA}(\rho_{CO}^{\tau_2})\ Generate\ new\ Offer\ (\rho_O^{\tau_3}),\quad Otherwise \tag{1}$$

During the negotiation process, the decision-making function f_D will estimate the utility value of offer or counteroffer as given in equation (2).

$$U_{ITBA}(\rho_{CO}^{\tau_2}) = \sum_{i=1}^{n} \quad w_i * \rho_{CO}^{x_i} \tag{2}$$

Let $\rho_{CO}^{\tau_2} = \{\rho_{CO}^{x_1}, \rho_{CO}^{x_2}, \dots, \rho_{CO}^{x_n}\}$ denote the number of preferable negotiation attributes available in the counteroffer, and w_i represents the weight factor of i^{th} negotiation attribute. Next, the negotiating parties' success rate can be estimated as the degree of acceptance expressed in equation (3).

$$\eta(ITBA_i, SPA_i) = \frac{ITBA_i^{Success} + SPA_i^{Success}}{ITBA_i^{Total} + SPA_i^{Total}} \tag{3}$$

Where $ITBA_i^{Success}$ and $SPA_i^{Success}$ represents the number of $ITBAs$ and $SPAs$ that reach the negotiation consensus. Similarly, $ITBA_i^{Total}$ and SPA_i^{Total} denotes the total number of $ITBAs$ and $SPAs$ involved during the negotiation process.

3.2 Cognitive fuzzy-based behavioral learning negotiation strategy

A sequence of negotiation offers exchanges between the parties $\rho^{\tau} = \{\rho_O^{\tau_1}, \rho_O^{\tau_3}, \dots, \rho_O^{\tau_{k-1}}\}$ can update its multi-attribute values $\{x_1, x_2, \dots, x_n\}$ of each offer by the proposed cognitive fuzzy-based negotiation strategy in the form of intervals such as $\rho_O^{\tau_1} = \{\rho^{[x_1^-, x_1^+]}, \rho^{[x_2^-, x_2^+]}, \dots, \rho^{[x_n^-, x_n^+]}\}$. Similarly, the sequence of counteroffers $\rho^{\tau} = \{\rho_{CO}^{\tau_2}, \rho_{CO}^{\tau_4}, \dots, \rho_{CO}^{\tau_k}\}$ generated by the opponent agent during the negotiation process can be modeled as $\rho_{CO}^{\tau} = \{\rho^{[x_1^-, x_1^+]}, \rho^{[x_2^-, x_2^+]}, \dots, \rho^{[x_n^-, x_n^+]}\}$. These sequences of counteroffer behavior need to be learned periodically under uncertain conditions concerning multi-attributes. Consider the behavioral learning variable $b \in R$ is observed during the negotiation process under a discrete-time interval $\tau \in \{\tau_1, \tau_2, \dots, \tau_k\}$. Then, the sequence of observed behavior during the historical time series can be defined as $\{b^{(\tau)}\} = \{b^{(\tau_1)}, b^{(\tau_2)}, \dots, b^{(\tau_h)}\}$. Here, the primary objective of the proposed negotiation strategy is to predict the next behavioral value of time series such $\{b^{(\tau_h+1)}, b^{(\tau_h+2)}, \dots, b^{(\tau_h+P)}\}$, where P referred to the behavioral prediction horizon.

The proposed cognitive fuzzy-based negotiation strategy provides the nonlinear mapping between n inputs and m outputs. It maintains the knowledge base to determine the basic parameters of opponents' negotiation behavior that affects the broker agents' decision-making process. At each round, negotiation decision-making is done based on the degree of cooperation rate estimation by the parameters like relevance, belief, and valuation interest. A degree of relevance δ between the participants' offers can be computed as defined in equation (4).

$$\delta = 1 - \frac{d^{best}}{\frac{\left(\sum_{i=1}^{m} d^i - d^{best}\right)}{(m-1)}} \tag{4}$$

Let $d^{best} = Min(d^1, d^2, \dots, d^m)$ denote the order of minimum distance offers from them number SPAs. Higher the degree of relevance indicates the best offer and highest degree of cooperation among the negotiating opponents. The degree of belief $\beta \in [0,1]$ determines the negotiation break-off, such as $\beta = 0$ denotes no expected termination and $\beta = 1$ denotes the sudden termination concerning the period. Finally, the sigmoid function $V \in [0,1]$ is employed to find the valuation interest of provider agents as defined in equation (5).

$$V = \frac{1}{1 + e^{\frac{v_{best}}{2} - v_c}} \tag{5}$$

Where v_{best} represents the maximum valuation interest of provider agents, v_c represents the current valuation interest, $V = 1$ indicates the higher importance of valuation interest, and $V = 0$ indicates the opposing valuation interest of negotiating parties. Therefore, the number of fuzzy rules is employed in this negotiation strategy according to the specified formation equation (6).

$$R_c = If\ \rho_{CO}^{x_{1c}}\ is\ A_{1c}\ AND\ \rho_{CO}^{x_{2c}}\ is\ A_{2c}\ AND\ \dots\ \rho_{CO}^{x_{nc}}\ is\ A_{nc}\ then\ \rho_O^{y_c} \tag{6}$$

The sequence of states obtained during the negotiation process can be formulated as a state transition function as $f_\tau(S_{\tau+1}|S_\tau, A_\tau)$. Based on the degree of cooperation among the negotiating agents, the proposed strategy decides to move from state S_τ to $S_{\tau+1}$ due to action $A_\tau \in \{A_{1c}, A_{2c}, \dots, A_{nc}\}$ taken at negotiation state $S_\tau \in \{S_1, S_2, \dots, S_n\}$. It can define a state transition probability from the state S_i to S_j by considering each action as a probabilistic event, as shown in equation (7). According to the transition function, the transition probability matrix (TPM) can be formulated as given in equation (8).

$$T_{S_i \to S_j}^{A_\tau} = P(S_{i\to j}, A_1) \times P(S_{i\to j}, A_2) \dots P(S_{i\to j}, A_n) \tag{7}$$

$$TPM = \left[T_{S_1\to S_2}^{A_1}\ T_{S_1\to S_2}^{A_2}\ :\ T_{S_1\to S_2}^{A_n}\ T_{S_2\to S_3}^{A_1}\ T_{S_2\to S_3}^{A_2}\ :\ T_{S_2\to S_3}^{A_n}\ \dots\ \dots\ \dots\ \dots\ T_{S_{n-1}\to S_n}^{A_1}\ T_{S_{n-1}\to S_n}^{A_2}\ :\ T_{S_{n-1}\to S_n}^{A_n}\right] \tag{8}$$

Let $\sum_{ij} T_{S_i\to S_j}^{A_\tau} = 1$ denote the total probability constraints. The linguistic terms of fuzzy variables belonging to a sequence of negotiation offers $\rho_O^{\tau} = \{\rho^{[x_1^-, x_1^+]}, \rho^{[x_2^-, x_2^+]}, \dots, \rho^{[x_n^-, x_n^+]}\}$ can be modeled as fuzzy membership functions as presented in equation (9).

$$\mu(x_i) = \{0 \quad if\ x \le p, \frac{x-p}{q-p} \quad if\ p \le x \le q,\ 1 \quad if\ q \le x \le r, \frac{s-x}{s-r} \quad if\ r \le x \le s, 0 \quad if\ x \ge s, \tag{9}$$

The parameters $p, q, r, and\ s$ could reflect in the membership function of negotiating parties belonging to the same linguistic terms differently. After receiving the offer or counteroffer, a negotiating agent, the degree of relevance, belief, and valuation interest parameters are measured based on the increasing and decreasing nature of fuzzy variables. In the case of offers observed from the negotiating parties may have different variable ranges indicating different types of responsiveness. For example, the variable range $(p = q = r < s)$ indicates the decreasing responsiveness, $(p < q = r = s)$ indicates decreasing responsiveness, $(p < q = r < s)$ indicates that the responsiveness increasing between p and q, and decreasing between r and s, $(p < q < r < s)$ reflects that the responsiveness increasing between p and q, reaches the maximum level between q and r, and decreasing between r and s. The proposed fuzzy-based behavioral learning system helps the negotiation strategy to prioritize the fuzzy constraints enforced during the concession made by parties against the various possible values of multi-issue applied in the e-commerce applications. Moreover, it helps to minimize the risk involved during trade-off and also minimize the quantity of information revealed during negotiation process to reach maximum agreement.

4 Experimental Evaluations

An agent-based automated cloud service negotiation framework is simulated using the JADE toolkit. In the simulation platform, a set of SCAs and SPAs are created with their respective negotiation preferences and the deadline for starting the bargaining process. Here, the ITBAs are made to negotiate on behalf of SCAs to maximize the utility value and success rate of SCAs. The negotiation strategies like linear, conciliatory, and conservative concession were exploited among the SPAs. Similarly, the SCAs exploit the same negotiation strategies and the proposed cognitive fuzzy-based negotiation (CFN) strategy. An experimental setting is made for ITBAs and SPAs with a set of input parameters containing price, time-slot, and negotiation strategy as given in Table 1. Based on these input parameters, the actual negotiation process is started in the simulator to mimic the real-time e-commerce negotiation in the cloud trading negotiation market. During the negotiation process, all the agents will automatically generate the sequence of offers and counteroffers based on the negotiating parties' preferences [28].

Table 1. Input parameters of ITBAs and SPAs

Input parameters	**ITBAs Settings**	**SPAs Settings**
Expected price	[10,60]	[200,250]
Reserved price	[200,250]	[10,60]
Expected time-slot	[10,60]	[300,350]
Reserved time-slot	[300,350]	[10,60]
Negotiation deadline	[50,200] Round	[50,200] Rounds
No. of negotiating agent	[5,20]	[5,20]
Negotiation strategy	Linear concession, Conciliatory concession, Conservative concession, Cognitive fuzzy-based negotiation strategy	Linear concession, Conciliatory concession, Conservative concession

To evaluate the agent-based automated cloud service negotiation framework's performance, the simulation experiment is conducted to measure the proposed CFN strategy's performance with various combinations of existing strategies like linear, conciliatory, and conservative concession [29]. The performance is measured in terms of utility value and success rate as shown in Table 2 and Table 3. The values given in these tables are normalized values of negotiation attributes. It is clear from the table; the proposed CFN strategy provides more utility value and success rate while comparing to other combinations of strategies applied during the negotiation process. Hence, the proposed CFN strategy outperforms the existing due to the opponents' learning capability, and decision-making logic, which makes appropriate concession-making during the sequence offers the generation process.

Table 2. Performance of negotiation strategies with respect to utility value

ITBAs Vs SPAs Strategies	Utility Value			
	50 Rounds	100 Rounds	200 Rounds	500 Rounds
Linear Vs Linear	0.163	0.327	0.557	0.755
Conciliatory Vs Linear	0.163	0.327	0.655	0.825
Conservative Vs Linear	0.163	0.393	0.393	0.393
Proposed CFN Vs Linear	0.895	0.985	1	1
Linear Vs Conciliatory	0.049	0.098	0.196	0.490
Conciliatory Conciliatory	0.049	0.098	0.196	0.490
Conservative Vs Conciliatory	0.049	0.426	0.426	0.426
Proposed CFN Vs Conciliatory	0.875	0.915	1	1
Linear Vs Conservative	0.491	0.721	0.721	1
Conciliatory Vs Conservative	0.491	0.983	1	1
Conservative Vs Conservative	0.491	0.557	0.557	1
Proposed CFN Vs Conservative	0.875	0.915	1	1

Table 3. Performance of negotiation strategies with respect to success rate

ITBAs Vs Strategies	Success Rate			
	50 Rounds	100 Rounds	200 Rounds	500 Rounds
Linear Vs Linear	0	0	1	1
Conciliatory Vs Linear	0	0	1	1
Conservative Vs Linear	0	1	1	1
Proposed CFN Vs Linear	1	1	1	1
Linear Vs Conciliatory	0	0	1	1
Conciliatory Conciliatory	0	1	1	1
Conservative Vs Conciliatory	0	1	1	1
Proposed CFN Vs Conciliatory	1	1	1	1
Linear Vs Conservative	0	1	1	1

Conciliatory Vs Conservative	0	1	1	1
Conservative Vs Conservative	1	1	1	1
Proposed CFN Vs Conservative	1	1	1	1

Table 4. Performance of negotiation strategies with respect to total negotiation time

ITBAs Vs Strategies	Total Negotiation Time (Minutes)			
	50 Rounds	100 Rounds	200 Rounds	500 Rounds
Linear Vs Linear	8.33	16.66	33.33	83.00
Conciliatory Vs Linear	6.66	13.33	26.66	66.00
Conservative Vs Linear	5.88	11.66	23.33	58.00
Proposed CFN Vs Linear	5.00	10.00	20.00	50.00
Linear Vs Conciliatory	6.66	13.33	26.66	66.00
Conciliatory Conciliatory	6.00	12.00	24.00	60.00
Conservative Vs Conciliatory	5.33	10.66	21.33	53.30
Proposed CFN Vs Conciliatory	4.66	9.33	18.66	46.60
Linear Vs Conservative	7.50	15.00	30.00	75.00
Conciliatory Vs Conservative	6.16	12.33	24.44	61.60
Conservative Vs Conservative	5.33	10.66	21.33	53.30
Proposed CFN Vs Conservative	4.33	8.66	17.33	43.3

Table 5. Performance of negotiation strategies with respect to communication overhead

ITBAs Vs Strategies	Communication Overheads (No. of Interactions)			
	50 Rounds	100 Rounds	200 Rounds	500 Rounds
Linear Vs Linear	100	200	400	1000
Conciliatory Vs Linear	80	160	320	800
Conservative Vs Linear	75	150	300	750
Proposed CFN Vs Linear	60	120	240	600
Linear Vs Conciliatory	80	160	320	800
Conciliatory Conciliatory	70	140	280	700
Conservative Vs Conciliatory	72	144	288	720
Proposed CFN Vs Conciliatory	55	110	220	550
Linear Vs Conservative	75	150	300	750
Conciliatory Vs Conservative	72	144	288	720
Conservative Vs Conservative	68	136	272	680
Proposed CFN Vs Conservative	52	104	208	520

The incorporation of agent-based technology in the development helps to manage the concurrent multi-issue negotiation among the multiple negotiation parties. It will easily overcome the sequential negotiation adapted in the traditional negotiation systems. The performance improvement achieved in this research study is due the inclusion of agent-based technology and cognitive fuzzy-based behavioral learning approach. To further analyze the performance of the proposed approach, the total negotiation time and communication overhead (number of interactions) involved during negotiation process are also considered [30]. So, the measurement of total negotiation time and communication overhead are computed during experimentation with respect to various negotiation strategies as stated in Table 4 and Table 5. More clearly shown that, the proposed cognitive fuzzy-based behavioral learning strategy takes very less total negotiation time and communication overhead while comparing to existing strategies [31] [32]. This significant improvement is possible due to more coordination among the negotiating parties by quickly reaching the consensus during negotiation process. In future, this study can enhance the performance of proposed negotiation system using effective attribute selection [33], and multi-level thresholding mechanisms [34] in the fog-cloud combined platform [35].

5 Conclusion

A cognitive fuzzy-based behavioral learning strategy is introduced in the multi-agent system platform to enhance sustainable development over the multi-attribute negotiation in e-commerce applications. The proposed negotiation strategy is employed in the intelligent third-party broker agent to maximize the utility value and success rate among the negotiating parties. The proposed strategy also uses cognitive knowledge of negotiation states and the concession adjustment behavior during the negotiation process. The proposed negotiation strategy outshines the presented negotiation strategies in terms of performance, such as utility value and success rate, due to its cognitive fuzzy-based learning capability. It also minimizes the total negotiation time and communication overheads involved during negotiation process. The thorough analysis of the automated negotiation framework is then enabled to realistically assess the sustainable outcomes of various negotiation strategies in the practical context.

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