Adaptive Negotiation Strategies

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ABSTRACT
Adaptive negotiation strategies are the strategies that are used in the adaptive negotiation model. There are mainly three adaptive negotiation strategies Conceder, Constant, Boulware. These strategies depend upon the utility function and time deadline. The Adaptive negotiation strategies describes the behaviour of the buyer or the nature of the buyer. The nature of buyer depends on the experiences which are taken from seller's offered price. After observing the past experiences the buyer will negotiate the price and the negotiation takes place.

General Terms
Negotiation refers to a mutual agreement by both seller and buyer for purchasing of a product.

Agent is defined as a set of instructions, algorithms or information's which performs actions or gives the output according to the input.

Keywords
Adaptive negotiation; agents; regression analysis; Bayes' interface; Bayesian interface; Posterior Probability.

1. INTRODUCTION
The word negotiation emerged in the early 15th century from the Old French and Latin word 'Negociacion' and 'Negotiationem' means 'business, trade and traffic'. In late 1590s negotiation had been defined as to communicate in search of mutual agreement [1].

Negotiation is a process by which buyer and seller communicate with each other to reach a profitable outcome. The outcome can be for both buyer and seller or just for one of the them. Negotiation is performed regularly in organizations, businesses and between governments. Negotiation process have some characteristics such as during negotiation there should be at least two parties, both buyer and seller should have pre-determined goals which they want to attain, both buyer and seller conceive that the result of the negotiation will be acceptable, during negotiation process buyer and seller ready for compromising, there is a belief of result by both the parties in any negotiation.

Negotiation is a process by which many group of agents do communicate with one another and try to form an agreement on something. It plays an important role in distribution of computation systems, e-commerce, grid computing and many more. However, there are many negotiation problems in real-world which involve interdependent multiple attributes and its utility functions are non-linear. To remove this limitation, a type of non-linear utility functions are been used. In the fields of e-commerce, grid computing, cloud computing and many more negotiation is applied as well as it captures human intuitions [2, 3].

In a multi-attributes negotiation, there is a way for finding a win-win agreement that cannot make one parties benefit better off without worsening those of the others. A negotiation system should be in such a way that it should be able to find win-win solutions because no one wants to leave mutual gain also multiple diverse solutions are required because when there are more options it will be easier to reach an agreement. A good win-win negotiation model should be efficient and which have a system that runs on bargaining mechanism. Such that it cannot treat any of the party differently on the basis of inappropriate criteria, for example which party goes first in the ongoing negotiation. A good negotiation model is that in which the participants are not asked to reveal much of their personal information. Thus, the users of negotiation agents can trust the models of negotiation and let the agents act on the behalf of them.

The problem is big when it involves multiple factors and multiple parties. To address this world wide problem various researches are done and many theories, concepts, algorithms and techniques are proposed for optimization of negotiations. This paper makes a review of work done and techniques developed so far in the domain of B2B e-commerce. The paper also looks toward fully automated system to business negotiations.

Such system consists of automated agents which can learn and subsequently provide effective negotiation strategies. These agents should able to be integrated into real e-commerce systems and provide negotiations automatically, efficiently and cost effectively.

In a win-win negotiation model and multi-objective genetic algorithm NSGA –II. Basically in this a set of agents and its opponents utility functions as two objectives. However, NSGA-II is centralized so it works only in that situation where the two utility function are public knowledge to both the sides in negotiation so we cannot employ NSGA-II straight forward in negotiation as if both sides would not like to let the other side or a third party known their private utility functions [4].

An adaptive agent means that there is an agent (machine) which adapts information, knowledge from the real world problems and then applies this in 'negotiation' process. Negotiation refers to a mutual agreement by both seller and buyer for purchasing of a product. Here, in this topic there is an adaptive agent negotiation technique for business to business e-commerce. E-Commerce refers to electronic commerce which deals with and selling of goods and services over the internet. There are various e-commerce websites in real world example Flipkart, Amazon [5].Both seller and buyer side there will be agent or there may be multiple agents which will perform negotiation between business to business enterprises on different issues which may include warranty, rating, quality, quantity, price etc.

2. LITERATURE REVIEW

A neural network approach to predicting price negotiation outcomes in business to business contacts .The research observe the antecedents of business to business price negotiation outcomes. Following are observed such as reservation price, target price, initial offering, profitability and size of relationship in this model. Predictive analytic approach given by a neural network is used for this research to observe business to business negotiations of a major chemical firm in Germany and its buyers. This research compared the result obtained from the neural network with multiple regression analysis. With the help of neural network problem of multicollinearity bias is solved and also provide more good predictions than the regression model [6].This research is involve in following examination:

a) Firstly, for companies, the result involve that it would be an intelligent thing to support sales personal in setting targets.
Also, companies could discuss an average target price or a price target for each customer.
Moreover, training clearly aimed to make negotiators to establish reasonable price targets and to defend them in negotiation.

b) Secondly, this research results discussed the change in price negotiation outcome better that existing experimental research.
Thus, depending on experimental data which receives too much stress on the importance of the initial offer seems to create a false effect.

c) Thirdly, this research observed that neural networks can be used to overcome networks can be used to overcome multicollinearity issues in data.

It also examined that the neural network analysis allows to predict the result with less error. This research suggests that neural network method may be used to wide range of business research problems where multicollinearity may be an issue.

Mukun Cao, Xudong Luo, Xin (Robert) Luo, Xiapoei Dai, proposed a goal based planed agent architecture provided with a multi-strategy selection model for automated negotiation system and also calculated its effects in the computer-computer negotiation experimentally [7].

This study performed three aspects:

Firstly, the goal based agent architecture had supported agent to choose an appropriate strategy by self to negotiate with the external environment without any human mediator when the negotiation starts.

Secondly, this research presents a multi-strategy selection model complete the research of negotiation strategy. The two methods which was used to design the negotiation strategy was the heuristic based approach and the machine learning approach.

Thirdly, with the bulky experiments, necessary knowledge based on experiences such as agents initial settings for negotiation strategy, reservation price and deadline for forming and using the human- computer negotiation system has been obtained [8].

Miguel A. Lopez- Carmona, Ivan Marsa-Maestre and Mark Klein told that for performing multi-agent negotiation, a consensus policy based mediation framework is used. A mechanism known as mediation mechanism was also proposed by this paper which was used to perform the exploration of negotiation space in the multiparty negotiation setting. The working of mediation mechanism is under the counselling of aggregation of agent performance and on the set of alternatives the mediator proposes in each negotiation round [9].

Mikoto Okumura , Katsuhide Fujita proposed, a collaborative park-design support system which is an instance of collective collaboration support system of collective collaboration support system basically dependent an multi-agent systems. In such system, agents collect the information of the user, many alternatives and reach to an optimal decision using negotiation protocol. The users attribute space and utility space in real would is decided in this paper. The user gives feedback in the last of the system. On the basis of the user's feedback, the alternative is ferial only if most of the users agree on some alternatives [10].

Ivan Marsa-Maestre, Miguel A. Lopez-Carmona and Mark Klien showed a framework for generalisation of negotiation process and for characterization as well. A set of metrics to calculate high level scenario parameters is provided. A framework is again presented to generate scenario in a parametric and reproducible way. Aggregation of hyper sound which is used to generate utility functions is the basis of generators. Generators are moreover, based in the uses of shared hyper volumes and also non-linear regression which is used to generate negotiation scenarios [11].

Moustapha Tahir Ateib had shown a fuzzy logic based negotiation modelling which can be used for overcoming the automation negotiation process complexity. To cope with ambiguity and uncertainty, this system used fuzzy logic [12].

Yan Kong, Minjie Zhang proposed a method which come to be known as negotiation based method which was used for the allocation of task under time constraints in an environment of open and dynamic grid. Both consumers and providers agents can enter into on exit the environment freely at any time in such type of environment. There was no central controller so that agents were negotiating with each other for allocation of task based on local uses [13].

Hsin Rau, Chao-Wen Chen , Wei-Jung Shiang designed a negotiation model, used for supply chain with one supplier and buyer. The model was useful for obtaining coordination under incomplete information environment. An objective programming approach is applied for finding an optimal solution [14].

Mukhopadhyay et. Al. recently proposed related solutions in negotiation over the internet for negotiation prediction and for efficient E-Commerce [15].

3. THEORETICAL STUDY

3.1 Regression Analysis

Regression analysis is the method used for estimating the relationships between different variables. It includes many techniques for analysing and modelling of different variables when the relationships is between a dependent variables and one or more independent variables. Mostly the regression analysis is used for the predicting and forecasting when there is a overlapping with the area it has been used if machine learning. There are many techniques used for imposing the regression analysis that are:

i. Linear analysis

ii. Ordinary least Squares regression

iii. Non parametric regression

Basically the performances of the regression analysis method depends upon the data generating process and how the approach being used to get the regression analysis [16].

The word ‘Regression’ was given by Francis Galton in nineteenth century which was used to describe a biological phenomenon i.e. when the heights of descendants of tall ancestors tend to regress down towards a normal average. For Galton the word regression was only the biological method but later on it was been extended by the Udny Yule and Karl Pearson [17]. Regression models involve the following variables such as:

a) *Unknown Parameters:* It is denoted byβ. It may represent scalar or vector.

b) *Independent Variables:* It is denoted by$X$.

c) *Dependent Variables:* It is denoted by$Y$.

Regression analysis is define as the method of predictive modelling technique which find the relationship between a dependent and independent variables. It is the important tool for modelling and analysing data. There are many uses of regression analysis such as:

- *Significant relationship:* These are those relationships which are between dependent variables and independent variables.
- *Strength of impact:* In this the strength of impact is been tested of multiple independent variables on a dependent variables.

Regression analysis allows the comparison of effects of variables measured on different scales [18, 19].

There are following types of regression analysis such as:

3.1.1 Linear Regression

In linear regression there must be a linear relationship between independent and dependent variables. Multiple regression gets affected by multicollinearity, autocorrelation, heteroscedasticity. Linear regression is very sensitive to outliers as it can be affect the regression line and the values that had been estimated.

3.1.2 Logistic Regression

Logistic regression is basically used to find out the probability of success and failure. It is mostly used for classification problems. It doesn’t require any linear relationship between the dependent and independent variables as it can handle various types of relationships that are applicable to non-linear log transformation to the predicted odds ratio. It requires large number of samples with different sizes because maximum likelihood estimates are less powerful at low sample sizes that ordinary least square. When the values of dependent variables are ordinal then it is called ordinal logistic regression and when dependent variables are in multi class then it is called as multinomial logistic regression [20].

3.1.3 Stepwise Regression

Stepwise regression is that type of regression when we are dealing with multiple independent variables. It basically adds and remove predictors as needed.

3.1.4 Ridge Regression

Ridge regression is that type of technique which is used when the data suffers from multicollinearity. It lowers down the value of coefficients but doesn’t reaches zero which means no feature selection feature.

3.1.5 Elastic Net Regression

Elastic net regression encourages group effect in case of highly correlated variables as there are no limitations in the numbers of selected variables. It suffers double shrinkage.

3.2 Concession Strategy

Concession stands for the act of conceding or yielding as a right or point. Negotiation concession are also sometimes referred to as trade-offs or discounts , where one or more parties to a negotiation engage in conceding ,yielding or compromising on issues under negotiation and that are done whether willingly or unwillingly[21].

3.3 Bayesian Interface

Bayesian interface is a method of statistical interference in which Bayes’ theorem is used for the updating of the probability for a hypothesis. Bayesian interface has found the many applications in many activities such as science, engineering, philosophy, medicine, sport and many more. Bayesian interface is also called the Bayesian Probability [22, 23].There are some points in Bayesian interface that have to remember while using it:

a) Prior distribution is the distribution of the parameters before any data has been observed.

b) Prior distribution may not be easily determined.

c) Sampling distribution is the distribution of the observed data conditional on its parameters.

d) Marginal likelihood is the distribution of the observed data marginalized over the parameters.

e) Bayesian theory is used for the prediction of the interface i.e. the distribution of the new unobserved data points.

3.4 Bayes’ Theorem

Bayes’ Theorem is also called as Bayes’ Law or Bayes’ Rule. Bayes’ Theorem describes the probability of the event which is based on the conditions. For example, if cancer is related to age then using Bayes' theorem the age of the person can be used more accurately. Bayes' theorem has many applications, but most importantly application is the Bayesian interface which is the exact approach to statistical interface. Bayes' theorem was the term given by Thomas Bayes (1701-1761), who studied how to compute a distribution for the probability parameter of a binomial distribution. He noted that by modern standards, we should refer to the Bayes price rule. Price discovered Bayes' work recognized its importance, corrected it, contributed to the article, and found a use for it [24].

4. METHODOLOGY

4.1 Time dependent bilateral Negotiation Model

Let i ($i \in \{b, s\}$) represents a negotiator.

Where,

$b =$ buyer agent

$s =$ seller agent

Both agents have

IP_i : Initial Price

RP_i : Reservation Price

So interval $[IP_i, RP_i]$ is range of all possible agreements. The interval can be normalized to [0, 1] using linear utility function:

$$U_i(p_i) = \frac{p_i - RP_i}{IP_i - RP_i} \qquad i \in \{b, s\} \qquad (1)$$

Where p_i: Value of an offer in $[IP_i, RP_i]$ [1] Faratin.P. , Sierva , C. Jennings, N.R: Negotiation Decision functions for autonomous agents. Robotics and Autonomous System.

Agent i decreases its utility $U_i(t)$ under time constant. At beginning agent i has highest utility of 1 for initial price. Afterwards $U_i(t)$ decreases according to decision function (Polynomial Function)

$$U_i(t) = 1 - (\frac{t}{T_i})^{\beta} \qquad i \in \{b, s\} \qquad (2)$$

Where,

T_i : Deadline of agent i

β : Concession Parameter

4.2 Concession Strategies

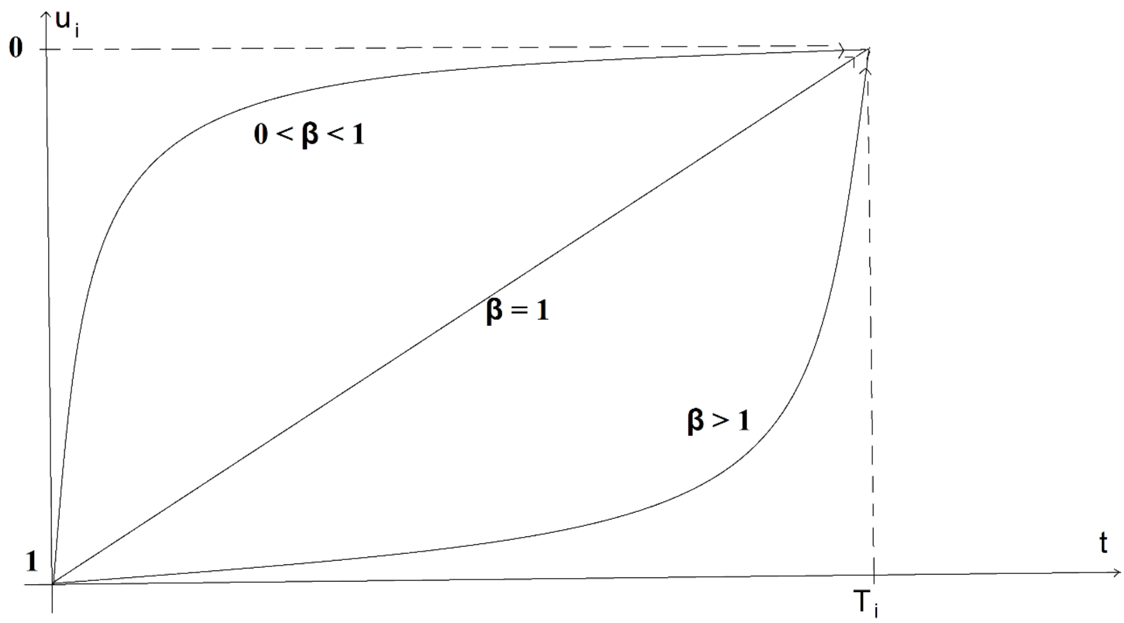

Figure 1: Concession Strategies

i. **Conceder:** $0 < \beta < 1$

Agent decreases utility at early and slowly at later stage.

ii. **Linear:** $\beta = 1$

This is the condition for constant when both the seller and buyer negotiate constantly.

iii. **Boulware:** $\beta > 1$

Slow concession at beginning and quick concession later.

Using value of, $U_i(t)$ can be calculated.

Counter offer that agent can give at time t

$$Offer_i(t) = RP_i + U_i(t)(IP_i - RP_i) \quad i \in \{b, s\} \quad (3)$$

Using equation 2 and 3,

$$Offer_i(t) = IP_i + (RP_i - IP_i)(\frac{t}{T_i})^{\beta} \quad i \in \{b, s\} \quad (4)$$

In Non-learning agents, values of β is not changed.

In learning agents value of β keeps on changing according to environment.

4.3 Adaptive Negotiation Model (Buyer-Agent)

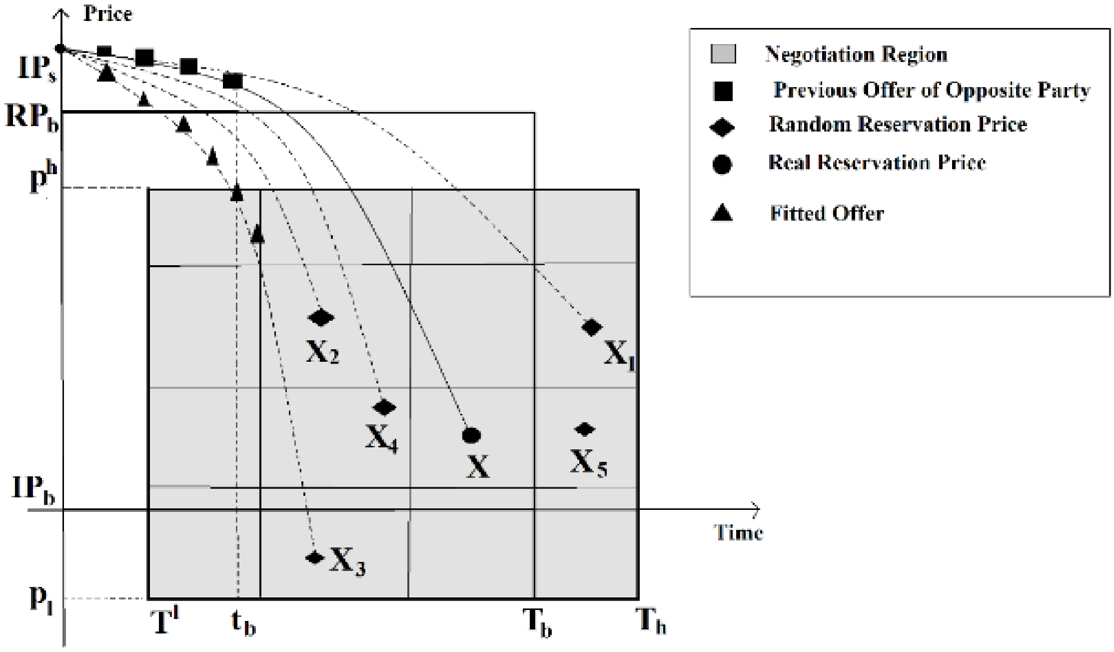

Figure 2: Adaptive Negotiation Model

Negotiation Block = (T^l, T^h, P^l, P^h)

Estimated by buyer from seller's history:

Where,

T^h, T^l : Estimated upper and lower boundaries of opponent deadline.

P^h, P^l : Estimated upper and lower boundaries of opponent's reserved price.

T_b : Buyer's Deadline

t_b = Current time in negotiation

IP_b, RP_b = Buyer's initial price and Reverse Price

IP_s = Seller's Initial Price

Negotiation block can be divided into N^t columns and N^p rows, creating

$N^t * N^p$ = N Total Negotiation Cells

A Cell $C_i (i \in 1,2, \dots \dots, N^t * N^p)$ can be denoted by

$$C_i = ({t^l}_i, {t^h}_i, {p^l}_i, {p^h}_i)$$

A random reservation point $X_i, ({t^x}_i, {p^x}_i)$ is a randomly selected point in each cell C_i

Where,

${t^l}_i < {t^x}_i < {t^h}_i$ And

${p^l}_i < {p^x}_i < {p^h}_i$

X_1, X_2, X_3, X_4 are random reservation points of opponent X is real reservation point (it maybe outside the negotiation region in real cases but the probability is more likely to be in the negotiation region).

Agent can guess approximate location of opponent's reservation point by learning from historical offers by renewing its belief about approximate location of reservation part.

4.4 Regression Analysis

Step1:

At round t_b , buyer selects random reservation point $X_i({t^x}_i, {p^x}_i)$ in each cell C_i.

Step2:

For each point $X_i({t^x}_i, {p^x}_i)$ of step 1 buyer calculates regression line l_i based on seller's historical offer $O_{t_b} = \{p_0, p_1, \dots \dots, p_{t_b}\}$ until foundt_b.

Using equation 4,

$$Offer_i(t) = p_o + ({p^x}_i - p_o)(\frac{t}{{t_i}^x})^b \quad (5)$$

Where,

p_o= Initial price of seller

b= Regression parameter work as concession parameter in utility function in equation 4.

Coefficient b can be calculated from seller's historical offers O_{t_b} as proposed in equation 2.

$$b = \frac{\sum_{i=1}^{t_b} t_i^* p_i^*}{\sum_{i=1}^{t_b} t_i^{*2}} \quad (6)$$

Ren.F. Zhang.M.J. Predicting Partmer's behaviour in negotiation by using Regression Analysis. In Zhang.Z, Siekmann, JH. (eds.)KSEM 2007 , LNCS(LNAJ), vol. 4788, pp 165-176 Springer, Heidelberg(2007).

Where:

$$p_i^* = l_n \frac{p_o - p_i}{p_o - p_i^x}$$

And

$$t_* = l_n \frac{t}{t_i^x}$$

Step 3:
Based on regression line l_i in step 2, buyer can calculate the fitted (predicted) offers

$\hat{0}t_b = \{\widehat{p_o}, \widehat{p_1}, \widehat{p_2}, \dots, \widehat{p_{t_b}}\}$ at each round.

Step 4:
Coefficient of Correlation,

$$\gamma = \frac{\sum_{i=1}^{t_b}(p_i - \bar{p})(\widehat{p_\iota} - \hat{p})}{\sqrt{\sum_{i=1}^{t_b}(p_i - \bar{p})^2 \sum_{i=1}^{n}(\widehat{p_\iota} - \hat{p})^2}}$$

Where $\hat{p}$ = Average value all fitted offers till time t_b

$\bar{p}$= Average value of all historical offers of seller

γ= Non Linear correlation with ($0 \le r \le 1$) shows non linear similarity between fitted an historical offers.

γ is criteria to calculate resemblance between Random Recollection Point and Seller Reservation Point V.

4.5 Bayesian Interface

Bayesian interface drives the posterior probability as a consequence of two antecedents or prior probability and likelihood function derived from statistical model for the observed data. Bayesian Interface computes the posterior probability according to Bayes' theorem:

$$P\left(\frac{H}{E}\right) = \frac{P\left(\frac{E}{H}\right).P(H)}{P(E)} \qquad (7)$$

Where,

A/B = A Given B
H= Hypothesis
E= Evidence Corresponding to new data
P (H) = Prior Probability before the data E
$P(\frac{H}{E})$= Posterior probability (after E is observed)

$P(\frac{E}{H})$= Probability of E Given H.
As a function of Ewith H fixed i.e. the likelihood.

Likelihood is a function of E.

Posterior probability is a function of H.

P (E) = Marginal Likelihood.

General Formulation:

$$P\left(\frac{M}{E}\right) = \frac{P\left(\frac{E}{M}\right)}{\sum_m P\left(\frac{E}{M_m}\right)P(M_m)}.P(M) \qquad (8)$$

Where,
$P(M_m)$= A set of initial prior probability$E \in \{E_n\}$. For each$M \in \{M_m\}$, the prior P (M) is updated to the posterior$P(\frac{M}{E})$.

4.6 Bayes' Interface

The hypothesis is defined as $H_i = (i \in 1,2,3, \dots, N_{total})$ where N_{total} is total number of cells in negotiation region. Each hypothesis H_i stands for the assumption that seller's reservation point X is in cellC_i.

The Prior Probability distribution $P(H_i), (i \in 1,2,3, \dots, N_{total})$ signifies the agent's belief about the hypothesis i.e. likelihood of hypothesis in real situation.

Initially $P(H_i) = \frac{1}{N_{total}}$ can be used after each round t_b probability of each hypothesis can be altered by Bayes' Theorem.

$$P\left(\frac{H_i}{o}\right) = \frac{P(H_i)P(\frac{O}{H_i})}{\sum_{k=1}^{N_{total}} P\left(\frac{O}{H_k}\right) P(H_k)}$$

Where:
$P(\frac{O}{H_i})$= Likelyhood of outcome O on hypothesisH_i.

Our observed outcome O is opponent's historical offers.

$$O_{tb} = \{p_o, p_i, \dots, p_{tb}\}$$

$P(\frac{O}{H_i})$ is likelihood of seller's historical offer O_{tb} on hypothesis H_i(i.e. seller's reservation point X is in cellC_i.

Posterior probability $P(\frac{H_i}{O})$ is updated probability based on new offer at next round.

By comparing fitted (predicted) points $\widehat{O_{tb}}$on regression line of each random reservation point X_i with historical offerO_{tb}, condition probability $P(\frac{O}{H_i})$ is calculated.

More consistent predicted offer → Higher$P(\frac{O}{H_i})$.

The non-linear correlation coefficient γ represents difference between regression curve and opponents bidding sequences. We can use γ as Conditional Probability.

4.7 Adaptive Negotiation Mechanism

First to calculate β we have 4 cases-

- Point $b_o(t_o, p_o)$: Buyer's current offer at time t_o
- Point $b_T(T_b, RP_b)$: Buyer's reservation price at deadlineT_b
- Point $X_i(t_i^x, p_i^x)$: Random reservation point of seller
- Point $P(t_p, p_p)$: New offered price of buyer

Case 1: $(t_i^x < T_b)\ and\ (p_i^x > p_o)$

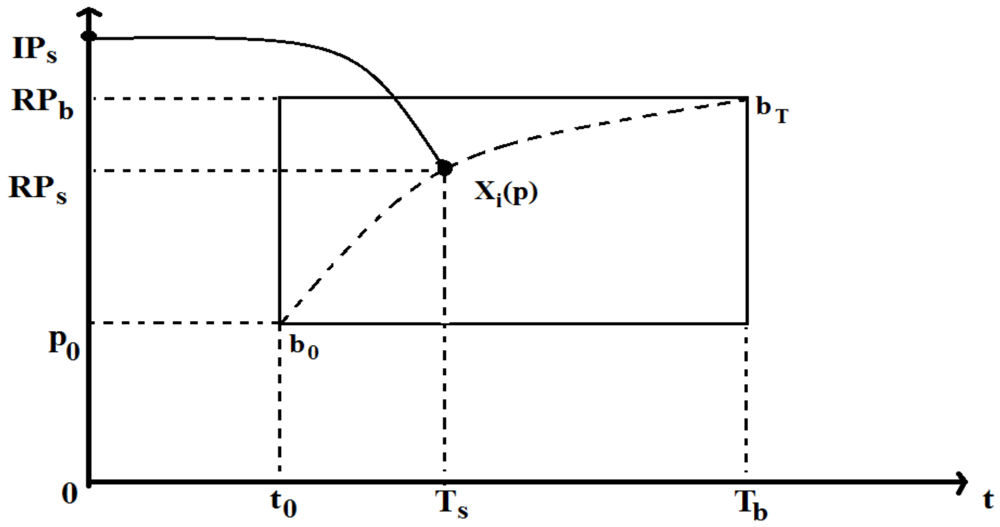

Figure 3: Graphical Representation for Case 1

Seller will quit at T_s at priceRP_s. So, buyer offer price P should be equal to $X_i(RP_s, T_s)$

Case 2: $(t_i^x > T_b)\ and(\ p_i^x \geq p_o)$

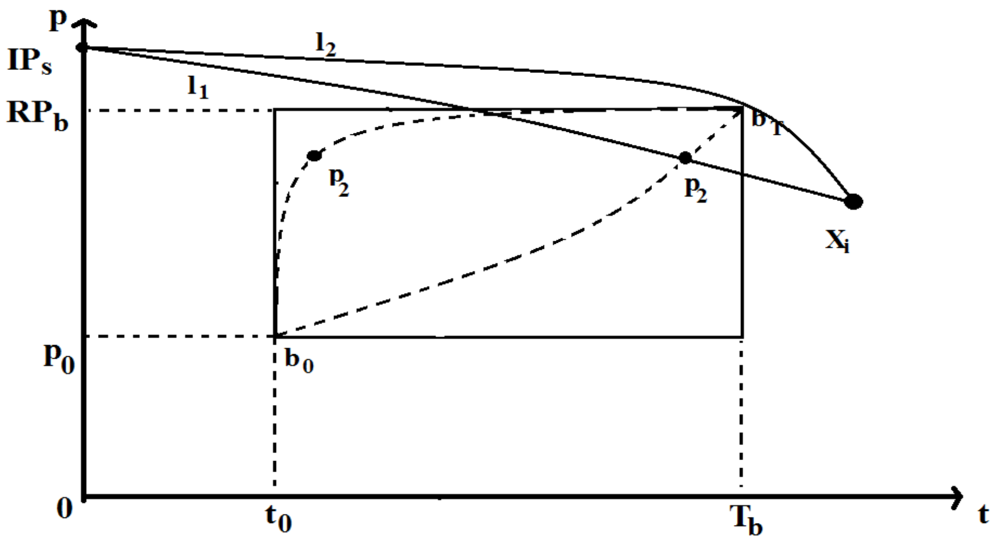

Figure 4: Graphical Representation for Case 2

Two regression lines$l_1\ and\ l_2$.

Linel_1: Buyer's negotiation line should pass through the intersection of l_1 and right boundary of buyer's negotiation region. So P_1 will be very close to buyer's deadlineT_b.

Linel_2: Negotiation will lead to fail, last offered price of buyer at reserve price of buyer RP_b and at buyer's deadlineT_b.

Point$P_2(t_o + 1, \emptyset_{max}.RP_b)$.

Case 3: $(t_i^x < T_b)\ and\ (p_i^x < p_o)$

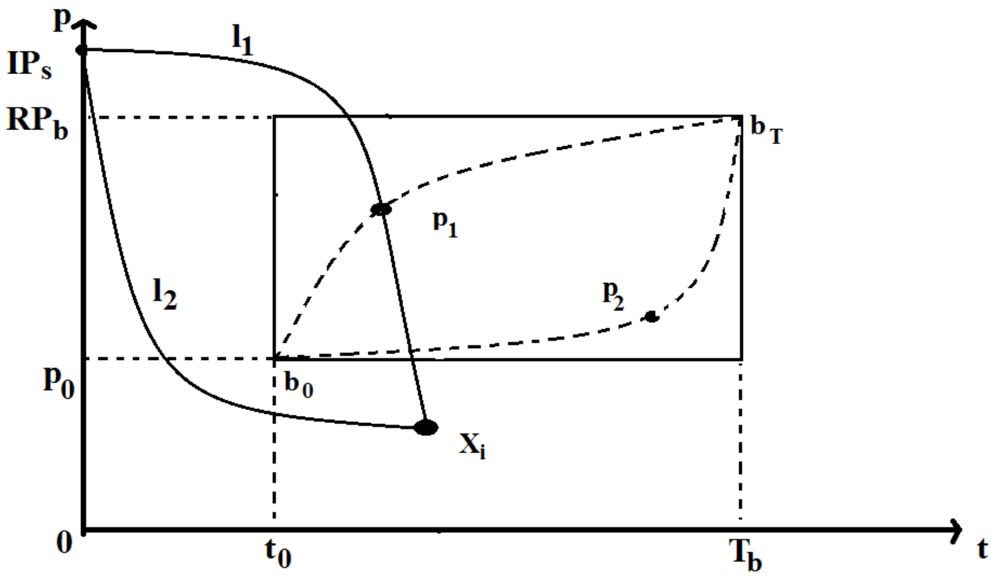

Figure 5: Graphical Representation for Case 3

Two regression lines l_1 *and* l_2.

Line l_1: Intersection of l_1 and bottom line of buyer's negotiation region. To calculate β set buyer's offer price P_1 one step earlier than intersection point at l_1.

Line l_2: l_2 do not pass through negotiation region. Keep price unchanged until $t_b - 1$ and give reservation price at deadline. To compute, set negotiation point P_2 very close to p_o.

Next price $(1 + \emptyset_{m,n})p_o$, where $\emptyset_{m,n}$ is close to 0 and $0 < \emptyset_{m,n} < 1$.

Case 4: $(t_i^x \geq T_b)$ *and* $(p_i^x \leq p_o)$

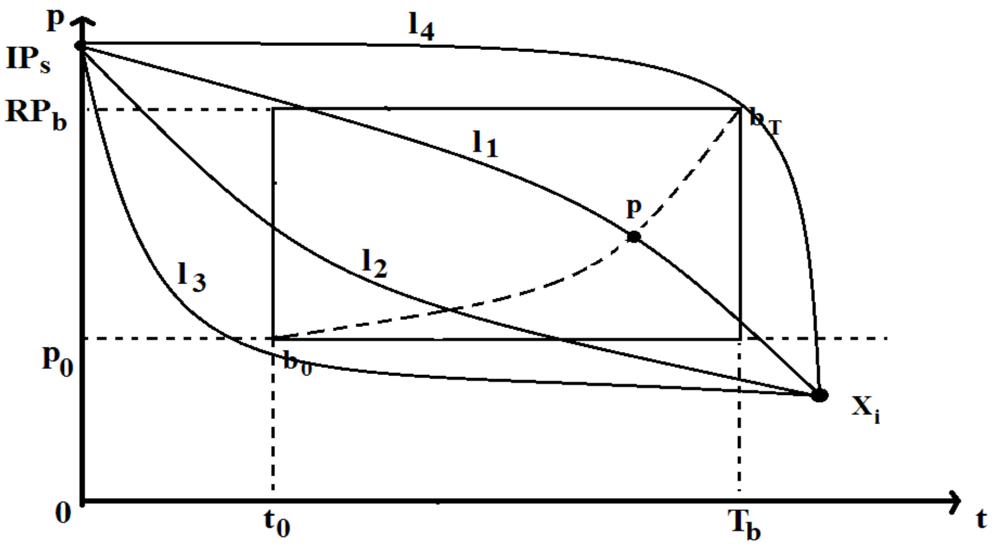

Figure 6: Graphical Representation for Case 4

Case 4 is the combination of Case 2 and Case 3.

4.8 Agent Mechanism

After calculating negotiation parameter β using equation (4) counter offer of buyer can be calculated by

$$Offer_b(t) = p_o + (RP_b - p_o)\left(\frac{t-t_o}{T_b-t_o}\right)^{\beta} \quad t > t_o \tag{9}$$

In above equation at time T_b buyer's offer will become the reserved price RP_b.

At given negotiation point $P(t_p, p_p)$, new value of parameter $\hat{\beta}$ can be calculated using equation (9),

$$\hat{\beta} = log_{\frac{t_p-t_o}{T_b-t_o}}\left(\frac{p_o-p_p}{p_o-RP_b}\right) \quad (t_o < t_p < T_b) \tag{10}$$

$\hat{\beta}$ is calculated for each random reservation point with a probability distribution

$$P(H_i) = \{P(H_1), P(H_2), \dots, P(H_n)\}$$

Let $\widehat{\beta_\iota}(i\epsilon\{1,2,\dots,n\})$ be estimated negotiation value for the negotiation point based on random reservation point in cell C_i.

$P(H_i)$ is the probability of $\widehat{\beta_\iota}$ which represents weighting proportion of corresponding $\widehat{\beta_\iota}$.

We can calculate concession area S_i i.e. area between negotiation line and time axis using value of $\widehat{\beta_\iota}$.

And concession area $\bar{S}$ related to overall negotiation parameter $\bar{\beta}$.

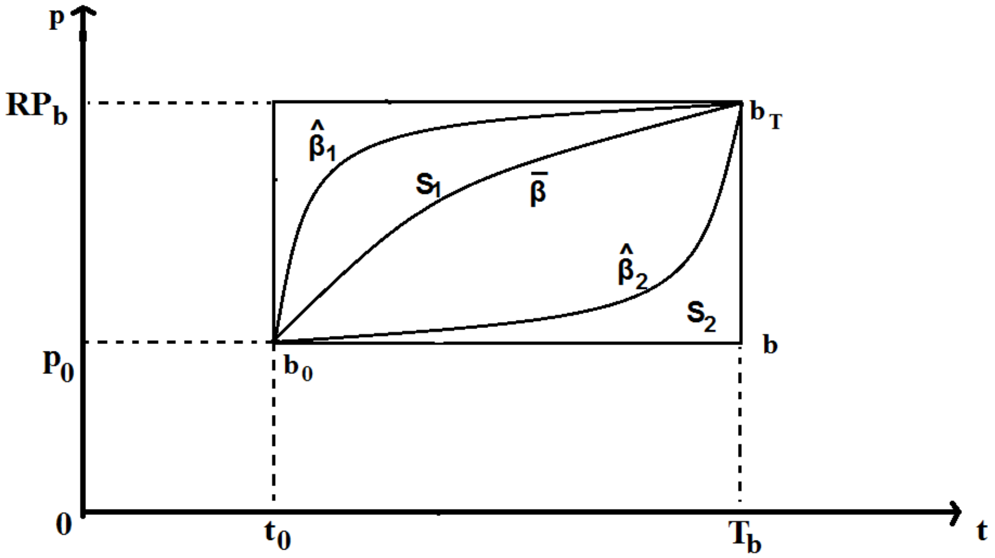

Figure 7: Agent Mechanism

From equation (9) we can get,

$$\bar{S} = \int_0^{T_b} [p_o + (RP_b - P_o)\left(\frac{t-t_o}{T_b-t_o}\right)^{\bar{\beta}}]dt \quad (11)$$

$$\sum_{i=1}^{n} P(H_i)S_i = \sum_{i=1}^{n} P(H_i) \int_0^{T_b} [p_o + (RP_b - P_o)\left(\frac{t-t_o}{T_b-t_o}\right)^{\widehat{\beta}}]dt \quad (12)$$

Since,

$$\bar{S} \sum_{i=1}^{n} P(H_i)S_i \quad (13)$$

Overall negotiation parameter $\bar{\beta}$ is,

$$\bar{\beta} = \frac{1}{\sum_{i=1}^{n} \frac{P(H_i)}{1+\beta_i}} - 1 \quad (14)$$

Buyer can set its negotiation parameter $\bar{\beta}$ to calculate counter offer according to equation (9) at each round of negotiation.

Each $\widehat{\beta_\iota}$ changes at each round according to randomly selected reservation point. The $P(H_i)$ is updated using Bayes' interface at each time. The value of $\bar{\beta}$ is updated at each round to make the process adaptive.

5. CONCLUSION

For any B2B business, negotiation is one of the most crucial stages. Automated and intelligent agent mechanism and web service implementation can be employed to develop advanced and dynamic e-commerce business systems to provide automated negotiation for both merchant and supplier. Negotiations in B2B domain are characterized as combinatorial complex negotiation spaces. It includes narrow negotiation deadlines and have little information about the opposite party in negotiation. There must be a practical negotiation mechanisms able to address these issues. Such web services and intelligent agents based automated negotiation system will address most of the requirements of a B2B e-commerce. This system should support multi-party negotiations having multiple issues.

6. RESULT

The experimental results of my work showed an improvement in the negotiation mechanism by providing higher utility value to the agent. Because in my model the agent continuously changes its concession rate according to the latest pattern of the opponent agent and behaves differently according to different scenarios. Our negotiation model dynamically adapts agent's negotiation strategy and reaches better negotiation price for the agent by learning from previous offers given by the opponent within same course of negotiation.

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