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An Optimized Approach for E-Commerce Negotiation

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***Abstract* — When business moved to the internet and the term e-commerce was coined, companies simply replicated traditional business practices. Negotiation is an important process of e-commerce activities. Its goal is to find the optimal solution satisfies buyers and sellers. This paper introduces an optimization technique for getting maximum profit for seller and also minimum cost for buyer. A model of e-commerce negotiation is proposed to find the optimal solution satisfying buyers and sellers, then an improved particle swarm optimization algorithm is used to find the best solution for negotiation. To prevent trapping into a local optima through increasing diversity of the swarm, uniform distribution method is used to generate initial particles. Experimental results show that using the proposed particle swarm optimization algorithm the negotiation solution has been improved.**

***Keywords* — PSO, E-Commerce, Recommender System, Optimization.**

I. Introduction

Internet as a tool of transferring data helps more industries to be more effective in their specialization. E-commerce as the next step after internet used for selling and buying which means the buying and selling of product or service over electronic systems such as the internet. Consumers can choose among millions of products in an online store, Instead of tens of products in a physical store. However vast amount of choices in this process increase the amount of data which make product selection difficult and time consuming [1][2]. To address this data overload and to overcome the traditional business drawbacks, many processes of business activities such as procurements, distributions and payments are electronic. But most of business negotiations are still processed in traditional ways. These ways could not meet the needs of increasingly frequent e-commerce. the challenging problem in e-commerce developing is to implement automatic e-commerce negotiation [3][4][17]. Kui et al., in [5] proposed an improved particle swarm algorithm to find the negotiation solution which is efficient in preventing being trapped in local optima. In this paper, the improved particle swarm algorithm has been applied to improve the efficiency of negotiation and decrease the cost of negotiation so as to match both buyers' and sellers' requirements.

The remainder of the paper is organized as follows: A briefed overview on particle swarm optimization and e-commerce is given in Section II. In Section III, e-commerce negotiation model is proposed, the improved particle swarm optimization algorithm to e-commerce negotiation is presented at the end of the section. Experimental results are discussed in Section IV. Finally, conclusions are given in Section V.

II. Background

In this section a brief introduction to the particle swarm optimization and e-commerce is given.

A. Particle Swarm Optimization (PSO)

PSO was inspired by the social behavior of a bird flock or fish school. In PSO algorithm, the birds in a flock are symbolically represented as particles. These particles can be considered as simple agents ”flying” through a problem space. A particle’s location in the multi-dimensional problem space represents one solution for the problem. When a particle moves to a new location, a different problem solution is generated. This solution is evaluated by a fitness function that provides a quantitative value of the solution’s utility [6][7][8]. Each particle represents a position in N_d dimensional space, and is ”flown” through this multi-dimensional search space, adjusting its position towards both the particle’s best position; found thus far and the best position in the neighborhood of that particle. Each particle *i* maintains the following information: x_i the current position of the particle, v_i the current velocity of the particle must be defined by parameters v_{min} and v_{max}. The personal best position of the particle is represented by y_i. So the particle’s position is adjusted according to

$$v_{i,k}(t+1) = w v_{i,k}(t) + c_1 r_{1,k}(t)\left(v_{i,k}(t) - x_{i,k}(t)\right) + c_2 r_{2,k}(t) y_k(t) - x_{i,k}(t) \qquad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (2)$$

Where w is the inertia weight whose range is [0.4, 0.9], c_1 and c_2 are the learning factors called, respectively, cognitive parameter and social parameter, $r_{1,j}(t)$, $r_{2,j}(t)$ □ $U(0, 1)$, and $k = 1, ..., N_d$. The velocity is thus calculated based on a fraction of the previous velocity, the cognitive component which is a function of the distance of the particle from its personal best position, and the social component which is a function of the distance of the particle from the best particle found thus far (i.e. the best of the personal bests). The personal best position of particle *i* is calculated as

$$y_i(t+1) = \begin{cases} y_i(t), & if\ f\left(x_i(t+1)\right) \geq f\left(y_i(t)\right); \\ x_i(t+1), & if\ f\left(x_i(t+1)\right) < f\left(y_i(t)\right) \end{cases} \qquad (3)$$

Two basic approaches to PSO exist based on the interpretation of the neighborhood of particles. Equation (1) reflects the globalbest (gbest) version of PSO where the neighborhood of each particle is the entire swarm. The social component then causes particles to be drown toward the best particle in the swarm. In the localbest (lbest) PSO model, the swarm is divided into overlapping neighborhoods, and the best particle of each neighborhood is determined so the social component of (1) changes to

$$c_2 r_{2,k}(t) y_{j,k}(t) - x_{i,k}(t) \qquad (4)$$

Where y_j is the best particle in the neighborhood of the i^{th} particle. The PSO is executed with repeated application of (1) and (2) until a specified number of iterations has been exceeded or when the velocity updates are close to zero over a number of iterations [9][7][10].

B. E-commerce

E-commerce is the buying and selling of products and services by businesses and consumers through an electronic medium, without using any paper documents. E-commerce is widely considered the buying and selling of products over the internet, but any transaction that is completed solely through electronic measures can be considered e-commerce. E-commerce is subdivided into three categories: business to business or B2B (Cisco), business to consumer or B2C (Amazon), and consumer to consumer or C2C (eBay).

The seller enters into negotiation with one or more of business partners, to see if they can agree mutually acceptable terms of business. Negotiation can be one-to-one, one-to-many or many-to-many, and as a result, many designed protocols have been used to handle this negotiation. Negotiation protocols determine the interchange of messages which take place during negotiation, and the rules by which the negotiators must abide. One-to-one protocols are simple automated negotiation between buyers and sellers which include the shop-front, where a seller simply o□ers a good at a fixed price, and iterated bargaining, with buyer and seller taking turns to exchange proposed agreements. One-to-many negotiation has been mostly automated using various kinds of auction mechanisms which include the English auction, the Dutch Auction and the Contract Net. Many-to-many protocols can be modeled as many one-to-one bilateral negotiations which include the Continuous Double Auction and the Call Auction [11][12][18][19]. Some example protocols in more detail can be seen in [13].

III. E-COMMERCE NEGATION MODEL USING PSO ALGORITHM

C. An E-commerce Negotiation Model

Negotiation takes place when a buyer (i.e., user) likes a product and there is at least some conflict of interest between the buyer and the seller. Negotiation is a process with the goal of intended benefit, in which the buyer and the seller bargain resources such as price, product features, etc. [14][15]. Both buyers and sellers have their estimation for every solution. The aim of negotiation is to find a solution that maximizes utility of both of them. In [5], Kui et al. denoted this problem as follows: Let i be the i^{th} negotiation solution that consists of many negotiation items. Let k be the k^{th} (k = 1, 2, ..., n) negotiation item. Let x_{ik} be possible value of the k^{th} negotiation item of the i^{th} negotiation solution, x_{ik} □ [min_k, max_k], where [min_k, max_k] is the interval of k^{th} negotiation item. Then, a negotiation solution is denoted as vector $X = (x_{i1}, x_{i2}, \ldots, x_{in})$.

Let U_k^s(X) and U_k^b(X) denote buyers' and sellers' utility function of the k^{th} item. Let w_k^b and w_k^s denote buyers' and sellers' weight value of the k^{th} item, where $\sum w_k^b = 1$and $\sum w_k^s = 1$. Buyers' and Sellers' utility assessment for solution X are defined in (5) as given in [5]

$$U_b(X)=\sum_{k=1}^{n} w_k^b\, U_k^b(X),\; U_s(X)=\sum_{k=1}^{n} w_k^s\, U_k^s(X) \qquad (5)$$

The goal of negotiation is to find a solution X which maximizes $U_b(X)$ and $U_s(X)$. In most situations, there is no solution that maximizes $U_b(X)$ and $U_s(X)$ at the same time because of profit conflict between buyers and sellers. Therefore, the goal function of e-commerce negotiation is proposed to be

$$MaxE\_Neg(X) = U_b(X) - U_s(X) \qquad (6)$$

D. An Improved PSO Algorithm for Negotiation Model

There are many techniques to find the optimal solution of e-commerce negotiation model presented in (6). In this paper, the improved PSO algorithm presented in [5] is used for the negotiation model. The original PSO algorithm as given in (1) and (2) would likely converge to local optima during the search process [7][15]. When all the particles collect at the neighborhood of an extreme point, each particle's velocity tends to vanish. If this is an extreme point, then it will be hardly possible to skip out the restriction area for all the particles, therefore the PSO algorithm convergence to the local optima. The convergence to local optima often occurs in the original PSO algorithm because its initial particles are randomly generated. To prevent the local optima, Kui et al., described the improved PSO algorithm in [5] by generating the initial particles in the swarm. The negotiation solution vector X could be view as a particle. The i^{th} initial particle is denoted as vector $X_i = (x_{i1}, x_{i2}, \ldots, x_{ik}, \ldots, x_{in})$, ($k$ = 1, 2, ..., n), where x_{ik} is initialized by Equation (7). Then all particles are uniformly distributed in the solution space.

$$x_{ik} = min_k + \frac{i(max_k - min_k)}{(N+1)} \qquad (7)$$

Proposed PSO algorithm for negotiation model is shown in algorithm (1).

Algorithm 1 Proposed PSO algorithm for negotiation model

Initialize x_{ik} using Equation (7)
Initialize randomly N, $MAXGEN$, w, c_1, c_2, p_i, v
  For each particle i **do**
   Calculate the $MaxE\ Neg(X_i)$ using Equation (6)
   If $Max\_\ Neg(X_i) \geq MaxE\ Neg(p_i)$ **then**
      $MaxE\_Neg(X_i) \leftarrow MaxE\_Neg(p_i)$
      If $MaxE\_Neg(p_i) \leq Max\_\ Neg(p_g)$ **then**
       $MaxE\_Neg(p_g) \leftarrow Max\_\ Neg(p_i)$
       Calculate v_i according to Equation (1)
       Calculate p_i according to Equation (2)
      End if
   End if
  End for
Return $MaxE\_Neg(p_g)$

IV. Experimental Results

The application of improved PSO algorithm in e-commerce negotiation is tested using Amazon datasets for cars [16]. Car Evaluation Database was derived from a simple hierarchical decision model. The Car Evaluation Database contains six input attributes: buying, maint, doors, persons, safety, boot. In this paper, only four attributes has been used: buying, doors, safety, boot. Which mean: overall price, price of the maintenance, number of doors, capacity in terms of persons to carry, the size of luggage boot, estimated safety of the car respectively. The parameters of PSO algorithm are defined as follows: N = 60, $MAXGEN$ = 30, w = 0.9, c_1 = 2, c_2 = 2. The experiment data of e-commerce negotiation is given in table I and table II. Which contain negotiation items, permissible range for each item and buyers' and sellers' utility functions. Five kinds of proposed simple utility functions are defined as follows from trading experiences:

$l(x_k) = (10x_k - min_k)/(max_k - min_k)$, where the larger the value of x_k, the larger the value of utility function.

$s(x_k) = (max_k - x_k)/(max_k - min_k)$, where the less the value of x_k, the larger the value of utility function.

$n(x_k) = (max_k - 5x_k)/(max_k - min_k)$, where the less the value of x_k, the larger the value of utility function.

$b(x_k) = (x_k - min_k)/(max_k - min_k)$, where the larger the value of x_k, the larger the value of utility function.

$m(x_k) = (5x_k - min_k)/(max_k - min_k)$, where the larger the value of x_k, the larger the value of utility function.

Table I : Negotiation items, permissible range and buyers' utility functions

Negotiation item x_k	Permissible range [min_k , max_k]	Buyers' utility	
		Weight	Utility function
x_1: price (dollars)	[1000(low) , 2000(v-high)]	0.1	$s(x_1)$
x_2: no. of doors	[2(doors), 5(or more)]	0.2	$s(x_2)$
x_3:safety (%)	[0(low), 1(high)]	0.5	$b(x_3)$
x_4: luggage boot size	[5(small), 10(large)]	0.2	$b(x_4)$

Table II : Negotiation items, permissible range and sellers' utility functions

Negotiation item x_k	Permissible range [min_k , max_k]	Sellers' utility	
		Weight	Utility function
x_1: price (dollars)	[1000(low) , 2000(v-high)]	0.19	$m(x_1)$
x_2: no. of doors	[2(doors), 5(or more)]	0.05	$n(x_2)$
x_3:safety (%)	[0(low), 1(high)]	0.6	$l(x_3)$
x_4: luggage boot size	[5(small), 10(large)]	0.25	$s(x_4)$

Fig. 1 shows the maximal fitness curves of the above e-commerce negotiation problem using both PSO and improved PSO algorithms. There is a tough increment at early iterations for both algorithms in Fig. 1. In the middle and later iterations the original PSO algorithm trapped into a local optima solution, while the improved PSO algorithm is more insusceptible to local optima solution, thus increasing the success rate of the algorithm. Meanwhile it has been observed that the value of fitness function has been increased after applying improved PSO, which means the utility function has been improved so both profit for seller has been increased and cost for buyer has been decreased so the buyers and the sellers are satisfied because both achieved their requirements.

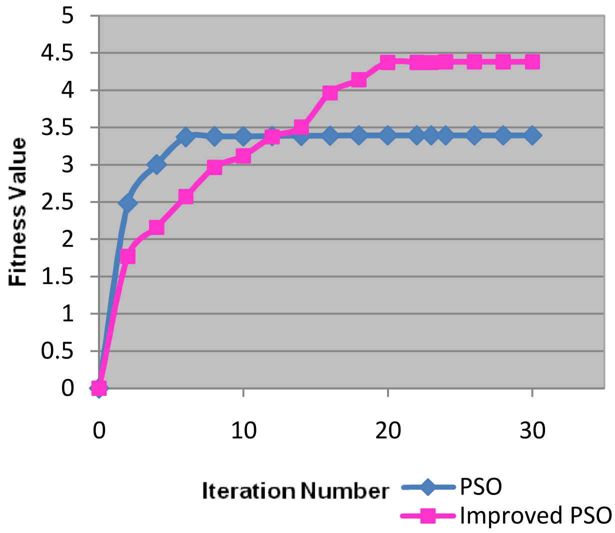

Fig.1. Maximal fitness curves

V. Conclusion

In this paper, an e-commerce negotiation model has been built to find the optimal solution satisfying buyers and sellers, then an improved particle swarm optimization algorithm is used to find the best solution for negotiation avoiding trapping into a local optima by generating the initial particles in the swarm. Experimental results indicate that the proposed model using improved PSO algorithm has good eect in e-commerce negotiation. As a future direction, the collective behavior and converged action of termites and nest-building of wasps could be fine tuned with their parameters to bypass certain local minima loops, while accomplishing e-commerce negotiation.

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