Priority based Matchmaking Method of Buyers and Suppliers in B2B e-marketplace Using Multi-objective Optimization

Xiaohui Li, Tomohiro Murata

***Abstract*—In this paper, we proposed a novel method to match buyers and suppliers in B2B e-marketplace based priority and multi-objective optimization. Analyzed matchmaking in a stable bilateral market, where each buyer or supplier is matched with trade partners. A mathematical model on many-to-many matching system as two objective optimization was developed to solve the multi-attribute matching problem. We attempted to apply priority based multi-objective genetic algorithm to seek optimal matching solutions, and illustrated the proposed matchmaking method. The results of simulation experiment demonstrated the proposed algorithm was flexible, it provided a set of solutions which including multiple optimal match solutions for decision-maker.**

***Index Terms*—Matchmaking, Multi-objective genetic algorithm, Priority, Pareto optimal.**

I. Introduction

Recent years, trading on the net is becoming diffusive quickly. Online business gradually came into use to replace conventional business. More and more commercial information interchange on the internet, there is a growing need for system that can deal with a variety of goods in B2B electronic marketplace.

Matchmaker, a system that matches demand and supply for one-to-many has existed. As a virtual middleman, matchmaker gathers useful information about products to purchase or sell and proposes efficient ways of making a contract to find the suitable trading partners. However, new application that matches buyers and suppliers with many-to-many manner automatically is not be widespread in B2B e-marketplace.

With the increasing availability of e-commerce, efficiency of transaction is the critical factor to be successful. Many-to-many e-marketplace will be gradually a mainstream in the future. Matchmaker will play a crucial role to find optimal match, it provides sufficient and flexible service for buyers and suppliers. As a result, many-to-many matchmaking method of exploration is great significance for the study of e-marketplace.

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II. Problem Description

Matchmaking is the process of searching the space of possible matches between demand and supplies. This process is by which parties that are interested in having exchange of economic value are put in contact with potential counterparts. Instead, it includes finding all the supplies that can fulfill the demand to some extent and identifying the most promising ones.

Matchmaker is a vital broker in B2B e-marketplaces, who will enable the most effective matches between requirements and proposals, will gain a competitive advantage and increase the acceptance and popularity of e-marketplaces. (as Figure 1)

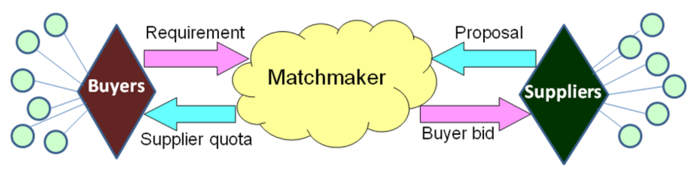


Fig. 1 Matchmaker in B2B e-marketplace

Generally, we can classify B2B e-marketplace two types. One is for a 1–N relationship such as an auction and bidding. The other is for an N–M relationship where there are many buyers and many sellers for a specific type of goods. N–M relationship is very efficient for the matchmaker in B2B e-marketplace.

For many-to-many matchmaking, matchmaker has two functions. One function is match buyer's preferences (such as "more is better" or "less is better") and supplier's capabilities (such as inventory). For example, if the buyer prefers that the more volume the better, matchmaker considers the volume factor is "more is better". Price is usually called "less is better" factor for the buyer. The other function is optimization. It is the process that extracts the most profitable trade for buyers and suppliers from feasible solutions.

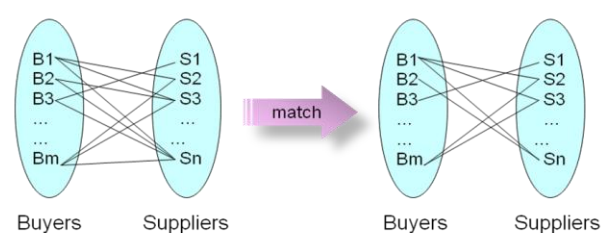


Fig. 2 Bipartite Graph matching

We conceive transform the finding trade partners problem into the bipartite graph matching problem. In figure 2, every edge means there is a matching relationship between buyer and supplier. The left bipartite graph is initial match. The right bipartite graph is optimal matching solutions. In this set, there are three eligible matching situations: 1) a buyer has match nexus with a supplier. 2) a buyer has match nexus with several suppliers. 3) several buyers have match nexus with a supplier.

III. Formulation as optimization problem

This is a multi-objective combinatorial optimization problem. The solving process for this problem includes **four phases: Analysis, Modeling, Implementation, Optimization.**

Phase 1 *Construct many-to-many architecture using bipartite graph.* In this phase, matchmaker identifies the attributes of buyers and suppliers, and screens out all eligible match schemes according to hard constraint;

Phase 2 *Design fitness function and establish mathematical model.* In this phase, matchmaker constructs the satisfaction function for both sides, and establish mathematical model;

Phase 3 *Solve model by priority based on multi-objective genetic algorithm.* In this phase, matchmaker uses a heuristic algorithm to solve this multi-objective optimization problem;

Phase 4 *Select optimal match solution to buyers and suppliers from Pareto set.* In this phase, matchmaker screens out the optimal match solutions set from feasible solutions, as possible as satisfied objectives of the two parties.

A. Constraint

The Constraint Satisfaction Problem (CSP) solver finds an optimal solution by choosing satisfied various preferential requirements for users. CSP techniques have recently been applied to many complicated problems in application areas such as operations research and artificial intelligence. They are very efficient in solving difficult problems, especially discrete combinatorial problems.

The considerable attributes were called constraints. The constraints are divided into two kinds of constraints: hard constraint and soft constraint. Hard constraint is represented in the form of an “equal to’’ notation and this constraint cannot be within the given scope of values. Soft constraint is represented in the form of inequality and this constraint can be relaxed within the given scope of values.

B. Mathematical Model

Many-to-many trade matching problem in our consideration, assumed there are i buyers and j suppliers in B2B e-marketplace. i means the number of buyers, i=1, 2,3,……,n. j means the number of suppliers, j=1,2,3,……,n. Buyers and suppliers consider several necessary factors. The requirement of buyer i for attribute f called constraint. The constraint usually classified two kinds: Soft constraint and hard constraint. Soft constraint includes “more is better” type attribute and “less is better” type attribute. Hard constraint is necessary conditions in the trade. It must be satisfied.

1) “More is better” type attribute

It means that the bigger attribute value the better is. The function $b_{igf} \in$ [-1, 1] shows that the fitness of buyer i for merchandise g for attributes f.

$$b_{igf} = \begin{cases} 1, & a_{gf} \geq e_{if} \\ \dfrac{a_{gf} - e_{if\,\min}}{e_{if} - e_{if\,\min}}, & e_{igmin} \leq a_{gf} < e_{if} \\ -1, & a_{gf} < e_{if\,\min} \end{cases}$$

2) “Less is better” type attribute

It means that the smaller attribute value the better is. The function $b_{igf} \in$ [-1, 1] shows that the fitness of buyer i for merchandise g for attributes f.

$$b_{igf} = \begin{cases} 1, & a_{gf} \leq e_{if} \\ \dfrac{e_{if\,\max} - a_{gf}}{e_{if\,\max} - e_{if}}, & e_{if} < a_{gf} \leq e_{if\,\max} \\ -1, & a_{gf} > e_{if\,\max} \end{cases}$$

In the above formulas, parameters explained as follows:

b_{igf} : *fitness function of buyer* e_{if} : *expected value*

a_{gf} : *the value of attribute f for merchandise g*

e_{ifmin} : *acceptable* min *value* e_{ifmax} : *acceptable* max *value*

3) Satisfactions function of buyer:

Matchmaker helps the two parties to find optimal trading partners by calculating satisfaction of buyers and suppliers. The function B_{ij} denotes that the satisfaction of buyer i for supplier j. Buyers usually consider several factors of merchandise. Therefore, it is a multi-criteria problem.

$$B_{ij} = \begin{cases} \sum_{f=1}^{k} w_{if} \times b_{igf}, & \text{when merchandise } g \text{ satisfied constraint} \\ -1, & \text{otherwise} \end{cases}$$

Buyer should set preferences for each soft constraint. The important degree of soft constraints for attributes f called preference coefficient. w_{if} shows the weight for each attributes f. It is satisfied normalization: $\sum_{f=1}^{k} w_{if} = 1,\ w_{if} > 0$. k means the number of soft constraint.

4) Satisfaction function of supplier

The function S_{ji} denotes that the satisfaction of supplier j for buyer i. Suppliers usually only care the bid of buyers. Therefore, it is a single criteria problem.

$$S_{ji}=\begin{cases}1, & p_{bi}\geq p_{sj}\\ \dfrac{p_{bi}-p_{sj\min}}{p_{sj}-p_{sj\min}}, & p_{sj\min}\leq p_{bi}<p_{sj}\\ -1 & p_{bi}<p_{sj\min}\end{cases}$$

In this formula, the meaning of parameters as follows:

p_{bi}: *the bid of buyer i* p_{sj}: *the quotation of supplier j*

Matchmaker calculates the buyers' satisfaction and suppliers' satisfaction for trading a commodity. Next, consider the buyers' requirement quantity and suppliers' provide quantity and calculate the trading volume. Multiplied the buyer's satisfaction with trading volume, matchmaker can get the total satisfaction of buyers and the total satisfaction of suppliers.

Establish mathematical model as the total satisfaction of buyer and total satisfaction of supplier two goals. Design of this model considered not only trading quantity, but also satisfaction of buyers and suppliers.

$$\max\sum_{i=1}^{n}\left(\sum_{j=1}^{m}x_{ij}B_{ij}*Q_{ij}\right)$$

$$\max\sum_{i=1}^{n}\left(\sum_{j=1}^{m}x_{ij}S_{ji}*Q_{ij}\right)$$

$$s.t\quad \sum_{j=1}^{m}x_{ij}\leq 1,\qquad i=1,2,......n$$

$$\sum_{i=1}^{n}x_{ij}\leq 1,\qquad j=1,2,......m$$

$$x_{ij}=\begin{cases}0, & \text{unmatch}\\ 1, & \text{match}\end{cases}$$

In this model, Q_{ij} is trading quantity between buyer and supplier. x_{ij}=0 means that there is match nexus between buyer i and supplier j. x_{ij}=1 means that there is not match nexus between buyer i and supplier j.

IV. Proposed Solving Method

A. Priority based multi-objective GA

This is a multi-objective combinatorial optimization problem. It exist multiple match solutions. In general, use conventional multi-objective optimization method to find only one solution. Multi-objective optimization problem is easy to find that almost every important real-world decision problem involves multiple and conflicting objectives which need to be tackled while respecting various constrains, leading to overwhelming problem complexity.

Genetic Algorithm(GA) is stochastic search algorithm based on the mechanism of natural selection and natural genetics. GA, differing from conventional search techniques, start with an initial set of random solutions called population satisfying boundary and system constrains to the problem. The central theme of research on GA is to keep a balance between exploitation and exploration in its search to the optimal solution for survival in many different environments. Features for self-repair, self-guidance and reproduction are the rule in biological systems, whereas they barely exist in the most sophisticated artificial systems.

Recently, GA has been received considerable attention as a novel approach to multi-objective optimization problems, resulting in a fresh body of research and applications known as evolutionary multi-objective optimization. There are three major advantages when applying GA to multi-objective optimization problems:

1) Adaptability: GA does not have much mathematical requirements about the optimization problems. Due to the evolutionary nature, GA will search for solutions without regard to the specific inner workings of the problem. GA can handle any kind of objective functions and any kind of constraints, *i.e.*, linear or nonlinear, defined on discrete, continuous or mixed search spaces.

2) Robustness: The use of evolution operators makes GA very effective in performing global search, while most of conventional heuristics usually perform local search. It has been proved by many studies that GA is more efficient and more robust in locating optimal solution and reducing computational effort than other conventional heuristics.

3) Flexibility: GA provides us a great flexibility to hybridize with domain dependent heuristic to make an efficient implementation for a specific problem.

The feature of the multi-objective GA is the multiple directional and global search by maintaining a population of potential solutions from generation. The next population comes from execute crossover and mutation operation for pre-population. Population-to-population approach is hopeful to explore all feasible solutions.

The feasible solutions chalk up by use the following algorithm:

Procedure: multi-objective GA
input: problem data, GA parameters
output: feasible solutions E
begin
  t := 0; // t: generation number
  initialize population P(t) by encoding;
  calculate objectives $f_i(p)$, i=1,2,……q by decoding;
  create feasible solutions E(p);
  evaluate eval(P) by fitness assignment routine;
  while (**not** terminating condition) **do**
    create offspring C(t) from P(t) by crossover operation;
    create offspring C(t) from P(t) by mutation operation;
    calculate objectives $f_i(c)$, i=1,2,……q by decoding;
    update feasible solutions E(P, C);
    evaluate eval(P, C) by fitness assignment routine;
    select P(t + 1) from P(t) and C(t) by selection routine;
    t := t + 1;
  output feasible solutions E(P, C);
end

Multiple match nexuses exist between buyers and suppliers. Therefore, from which buyer begins purchasing, match results are different. For the same buyer, from which supplier begins providing, match results are also different. Because supplier's providing capability are limited. If the first buyer bought all products from a supplier, the second buyer had to consider buying from other suppliers. Consequently, priority sequence of buyers and priority sequence of suppliers are necessary as calculating trading quantity.

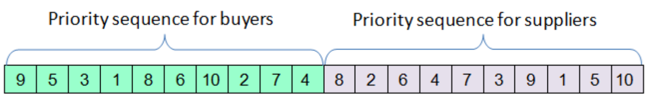
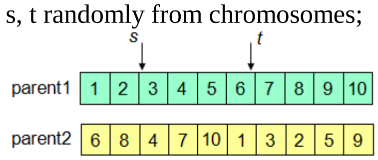


Fig. 3 Priority sequence chromosome

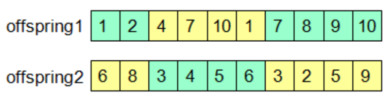
In Figure 3, the element of chromosome denotes priority. A chromosome corresponds to a feasible solution. Firstly, priority sequence random generated. Secondly, execute crossover and mutation operation for this priority sequence.
The executing process of crossover and mutation as following:

1) Crossover:

Step 1: select two chromosomes randomly as parent, and select two positions s, t randomly from chromosomes;



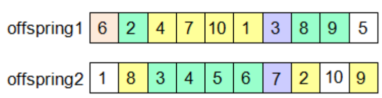
Step 2: exchange two substrings;



Step 3: determine the mapping relationship;

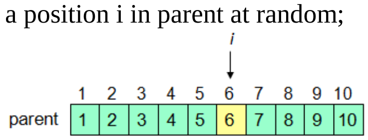
$1 \longleftrightarrow 6$
$10 \longleftrightarrow 5$
$3 \longleftrightarrow 4 \longleftrightarrow 7$

Step 4: legalize offspring.

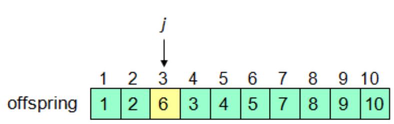


2) Mutation:

Step 1: select a position i in parent at random;



Step 2: insert selected value in randomly selected position j of parent.



After crossover and mutation operation, select the better individuals into the next generation operation. By several generations operating, the feasible solutions region is created.

B. Extraction of Pareto optimal set from feasible solutions

Multiple feasible solutions exist in the feasible region. Thereby, how to seek optimal solution is a considerable focus. Usually no single solution is optimum with respect to plural objectives of mutually conflicting at the time. We consider to get compromising solution that makes one objective function is optimal and other all objective functions close to the true optimal solution functions as much as possible. Consequently there is a set which includes multiple optimal solutions, known as Pareto optimal solutions set (conceptual model of two objective is shown in Figure 4), non-inferior solutions, or effective solutions.

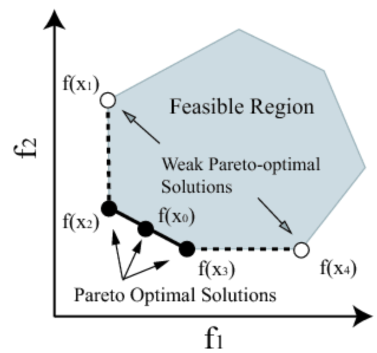


Fig. 4 Pareto optimal solution set

Each optimal solution is situated the Pareto front. Although not perfect, the multi-objectives GA find a very reasonable approximation to the Pareto front. Use the following algorithm to gain Pareto optimal solutions set.

```
Procedure: Pareto optimal solutions set based on multi-objective
input: data set(TB and TS),
output: Pareto optimal solutions set S*
begin
     i=0;    // i: the previous solution
     j=0;    // j: the next solution
     s[1, 2];  // feasible solution(TB,TS)
    if(i == j)  continue;
    if(((s[i, 1]>s[j, 1]) && (s[i, 2]>s[j, 2]))||
     ((s[i, 1]==s[j, 1]) && (s[i, 2]>s[j, 2]))||
      ((s[i, 1]>s[j, 1]) && (s[i, 2]==s[j, 2])))
    {
          S*=s[i, 1];  // select larger TB and TS
    }
    else if(((s[i, 1]>s[j, 1]]) && (s[i, 2]<s[j, 2])) ||
            ((s[i, 1]<s[j, 1]) && (s[i, 2]>s[j, 2])))
    {
        S*= s[i, 1];  // select TB and TS which unable be compare
    }
    else
    {  break; }
          i=i+1;    // continue compare
          j=j+1;
   output Pareto solutions set S*;
end
```

In Pareto optimal solutions set S*, each solution cannot be compared with other solutions. Select the max value of TB and the max value of TS as a ideal solution.

V. Simulation Experiment

A. Multi-objective many-to-many matchmaking

The following case is explanation of proposed many-to-many matchmaking method. We assumed in note-PC e-marketplace, there are ten buyers and ten suppliers. Buyers and suppliers consider six factors: Brand, Size, Configuration (CPU, Memory, Hard disk), Price, Delivery time, Quantity. Brand and Size are hard constraints. Other factors are soft constraints. For buyers, CPU, Memory and Hard disk are "more is better" type factors, Price and Delivery time are "less is better" type factors.

Matchmaker regards buyers' total satisfaction and suppliers' total satisfaction as goals, helps the two parties to find optimal trading partners. Table1 shows the requirements from note-PC buyers. Table2 shows the proposals from note-PC suppliers.

Table 1 Buyer's requirements

Buyer	Brand	Size	Config										Price (万円)			Delivery Time (Day)			Quantity
i		"	CPU (GHz) Min	Exp	w	Mem (GB) Min	Exp	w	HD (GB) Min	Exp	w	W	Max	Exp	W	Max	Exp	W	
B1	Sony	13.3	1.7	2	0.3	0.5	1	0.1	60	100	0.6	0.2	23	19	0.3	4	2	0.5	60
B2	Sony	13.3	1.5	2	0.3	1	2	0.1	80	100	0.6	0.2	22	20	0.3	4	3	0.5	20
B3	Sony	13.3	1.7	2	0.3	0.5	1	0.1	80	120	0.6	0.6	22	20	0.3	5	2	0.1	20
B4	Dell	14.1	1.6	2.2	0.6	1	1	0.3	80	120	0.1	0.5	21	19	0.3	5	2	0.2	90
B5	Dell	14.1	1.6	2.2	0.6	1	2	0.3	80	100	0.1	0.2	23	19	0.1	4	2	0.7	90
B6	IBM	14.1	1.6	2.2	0.3	1	1	0.1	60	100	0.6	0.2	21	20	0.4	5	3	0.4	50
B7	IBM	12.1	1.6	2.2	0.1	1	2	0.3	80	100	0.6	0.1	21	20	0.5	4	2	0.4	90
B8	IBM	14.1	1.5	1.8	0.1	0.5	1	0.3	60	100	0.6	0.4	21	18	0.5	5	3	0.1	90
B9	Dell	14.1	1.6	1.8	0.1	1	1	0.3	60	100	0.6	0.5	23	18	0.1	4	2	0.4	90
B10	IBM	12.1	1.5	1.8	0.6	0.5	2	0.3	60	100	0.1	0.5	23	19	0.2	5	2	0.3	90

Table 2 Supplier's proposals

Supplier j	Brand	Size "	CPU (GHz)	Memory (GB)	HD (GB)	Price (万円) Min	Expect	Delivery Time (Day)	Quantity
S1	Sony	13.3	2	0.5	60	17	20	4	30
S2	IBM	14.1	1.7	0.5	80	17	21	2	50
S3	IBM	12.1	2	2	120	19	20	4	100
S4	Dell	14.1	1.8	2	100	18	22	4	80
S5	IBM	14.1	2.2	1	120	18	23	3	100
S6	IBM	12.1	1.6	2	120	17	20	2	100
S7	Sony	13.3	1.8	1	100	19	22	3	30
S8	IBM	14.1	1.5	0.5	80	18	22	4	50
S9	Dell	12.1	1.8	1	80	19	22	3	80
S10	Dell	14.1	2.2	0.5	120	19	21	5	30

The proposed matching method includes six specific steps:
Step1: Identify the attributes of buyers and suppliers, and find all eligible matching nexuses;
Step2: Calculate respectively buyer's satisfaction and supplier's satisfaction according to fitness functions;
Step3: Compute trading quantity according to buyer's priority sequence and supplier's priority sequence;
Step4: Modeling as total satisfaction of bilateral goal;
Step5: Chalk up feasible solutions by using priority based multi-objective genetic algorithm;
Step6: Filtrates out Pareto optimal set from feasible solutions.

Figure 5 shows the feasible solutions after 500 generation computing. TB and TS are respectively two objectives: Total buyer's satisfaction and Total supplier's satisfaction. The blue point denotes the feasible solutions. The red point denotes the ideal solution.

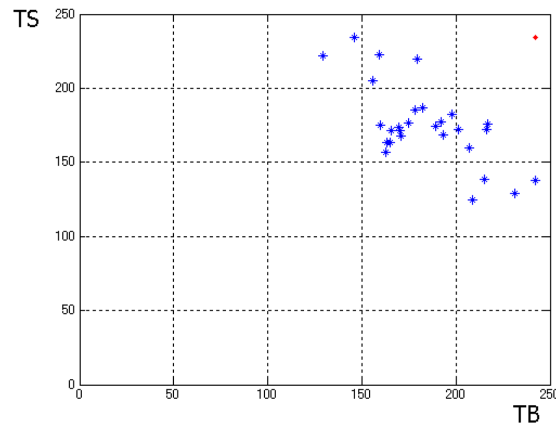


Fig. 5 Feasible solutions

Figure 6 shows the optimal solutions in Pareto set which pick out from feasible solutions set.

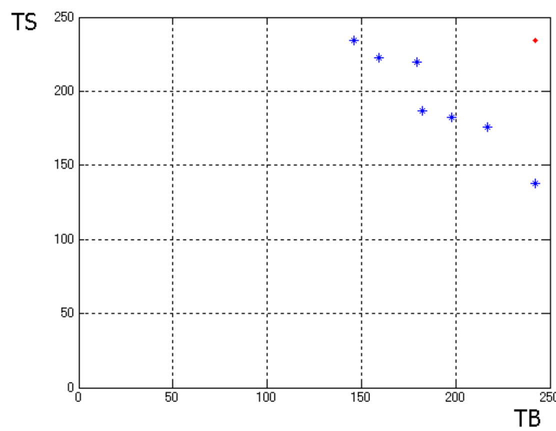


Fig. 6 Pareto optimal solutions

Without additional information, all these solutions are equally satisfactory. The goal of multi-objective optimal is to find as many of these solutions as possible. If reallocation of resources cannot improve one cost without raising another cost, then the set is Pareto optimal solutions.

Table 3 Pareto optimal set

Pareto optimal set	TB	TS
solution1	197.9667	182.5
solution2	159.2667	222.5
solution3	179.5	220
solution4	216.8533	175.8333
solution5	182.3	186.6667
solution6	242.2667	137.5
solution7	146.1533	234.1667

Simulation result demonstrates the proposed matchmaking algorithm was flexible. The algorithm can obtain the optimal solution in a short period of time. And this optimal solution will be closed to the ideal solution. Once this set of solutions is found, then matchmaker can select a solution based on various criterions. For instance, if matchmaker is neutrally, optimal solution will be the nearest to the ideal solution. According to calculating, the solution 4 (as Table 3) is optimal match solution, output corresponding match result as figure 7.

Fig. 7 One optimal matching solution

B. *Evaluation of calculation time*

For large-scale matchmaking problem, when the variable n is considerable, the general scale of the algorithm will encounter two difficulties: First, call for the calculation of a very long time; another computer's memory is not enough memory to store search terms required by the direction of the matrix.

Multiple buyers' requirements and multiple suppliers' proposals randomly generated. Respectively record the running time for match scales are from 10 to 1,000 (as Figure 8). Program and implement the proposed matching method by matlab7.0. The program run in the computer which configuration is CPU: Petium4 3.00 GHz, Memory: 1G. Matchmaker can choose suitable match scale according to the user allotted time.

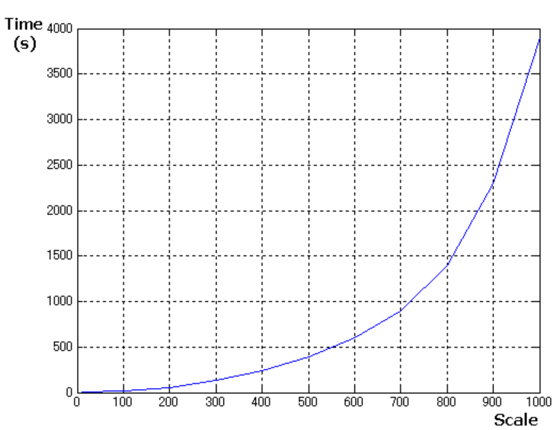


Fig. 8 Running time for different match scale

VI. Conclusion

We presented a novel method for many-to-many matchmaking in B2B e-marketplace, and a multi-objective mathematical model as maximize the duplex total utility is constructed. The trader's satisfaction function for multi-attribute commodity is proposed. By trying to use priority based multi-objective GA, get the feasible solutions. Seek Pareto optimal solutions from feasible solutions according different criteria, and conducted a simulation to verify the proposed matchmaking method. The results of simulation experiment demonstrated the proposed method was flexible and effectively for reducing the conflicts among design objectives and giving the maximal satisfaction degree. It provided multiple optimal matching solutions for matchmaker.

VII. Future Study

Future study will investigate the applicability of bilateral matching for business processes to multilateral process matchmaking. And will focus on develop a friendly interface for matchmaker and improve the computing time of proposed algorithm.

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