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Intelligent modeling method based on genetic algorithm for partner selection in virtual organizations

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The goal of a Virtual Organization is to find the most appropriate partners in terms of expertise, cost wise, quick response, and environment. In this study we propose a model and a solution approach to a partner selection problem considering three main evaluation criteria: cost, time and risk. This multiobjective problem is solved by an improved GA that includes meiosis specific characteristics and step-size adaptation for the mutation operator. The algorithm performs strong exploration initially and exploitation in later generations. It has high global search ability and a fast convergence rate and also avoids premature convergence. On the basis of the numerical investigations, the incorporation of the proposed enhancements has been successfully proved.

JEL Classifications: C61, C63, M21

Keywords: Virtual organization, partner selection, optimization, genetic algorithm.

Introduction

The "Virtual Organization" is defined in many ways (Ahuja et al., 1999; Bultje et al., 1998; Byrne, 1993; Hoogeveegen et al., 1999). It is rather a concept that was developed in a long process since the early 1990s. This concept is still evolving, the terminology is not yet fixed and even nowadays the Virtual Organization (VO) is named Virtual Enterprise (VE) in some papers. All the definitions are emerging to the following characteristics: the Virtual Organization is an alliance of separate firms (that function autonomously), interconnected, customer oriented, and acting together to take advantage of a market opportunity. When the market opportunity arises, the potential partners are meeting and negotiating through the information infrastructure, the Virtual Organization is created, the manufacturing processes are started and the product is completed. When the opportunity is exhausted or a new market opportunity occurs, the Virtual Organization can be reconfigured and so on until its mission is fulfilled and is finally dissolved.

In configuring a Virtual Organization, managing partner firms for a specific order or project is very important. Partner selection is not an easy task. It involves important decision making because it includes many factors to be taken into consideration: quality, cost, geographical limitations, delivery time, but also principles of human interaction: trust, communication skills, integrity, etc. As pointed out by Dickson (1966), multiple criteria have to be considered in order to select an appropriate set of partners for creation of a new VO. However, most often, the key factors to be addressed are grouped into three categories: structural compatibility goals, managerial compatibility goals, and financial goals (Famuyiwa et al., 2008).

Several attempts were made to create a general framework to map the relationships among the organizational units and the partnering companies (Camarinha-Matos et al., 2005; Stock et al., 2000; Fischer et al., 2004). The most relevant model is the Supply Chain

Operations Reference Model (SCOR) developed by the Supply Chain Council (<http://supply-chain.org/>). It is a process reference model for supply-chain management that translates qualitative performance in metrics (more than six hundred in last version). But as the VO environment continues to develop, applying qualification criteria for the evaluation of candidates is still a challenge.

Mathematical models and optimization methods for the partner selection problem have received much consideration from the research community. A well structured approach has been proposed by Talluri et al. (1999). They proposed a two-phase mathematical programming model based on data envelopment analysis (DEA) for designing value chain network. Phase one identifies efficient candidates for each type of business process and the second phase contains an integer goal-programming model to select an appropriate combination of partners based on a number of compatibility objectives. In line with their work, Li and O'Brien (1999) developed a model in supplier-buyer relationship and a linear programming technique to help managers consider both qualitative and quantitative factors in the purchasing activity in a systematic approach.

Wu et al. (1999) proposed a network integer program for the partner selection problem choosing one and only one candidate for each task of the production process. However, that model is restrictive and leads to the inflexibility of the network structure. In their related work on project scheduling, Brucker et al. (1999) integrated partner selection in the project scheduling problem. Al-Khalifa et al. (1999) and Tatoglu (2000) examined partner selection criteria using a typology that distinguishes between partner-related and task-related selection criteria. The task specific criteria relate to the operational skills and resources needed to ensure the viability of a proposed collaboration, while the partner related criteria relate to the effectiveness of cooperation and compatibility between the partners.

Using fuzzy approach, Mikhailov (2002) presented models that account for multiple criteria, such as organizational competitiveness and social relationships. Other researchers (Yang et al., 2007; Wang and Yang, 2007) have applied AHP (analytic hierarchical process) using ten factors in three main categories (risk, expectation and environment) to construct a model of the outsourcing problems.

Several other methodologies such as tabu search (Ko et al., 2001), branch and bound algorithm (Ip et al., 2004), and graph theory (Wu and Su, 2005) have also been proposed for partner selection. More recently, the studies on natural computing systems have shown that these algorithms (specially the evolutionary methods such as Artificial Immune Systems, Genetic Algorithms, Particle Swarm and Differential Evolution) can be efficiently used to eliminate most of the difficulties of classical methods and are suited to deal with the problem at hand.

In this study we propose a model and a solution approach to a partner selection problem considering three main evaluation criteria: cost, time and risk. This multiobjective problem is solved by an improved GA that includes meiosis specific characteristics and step-size adaptation for the mutation operator.

Problem formulation

Assume an enterprise wins a large project that can be divided in several sub-projects and each sub-project is called for bid to select one or more tenders. All the potential partners are expressed with the information obtained from the bidding process regarding the internal running cost, reaction time and running risk. The link time and cost between candidates are also given.

Based on the bidding information from candidate enterprises, the best candidate enterprise portfolio can be determined.

Following commonly used notation (Zhong et al., 2009), assume a certain project consists of J business processes (core competencies). For the j^{th} business process there are I_j potential candidates for the partners. Let u_i^j , $i=1, \dots, I_j$ be the i^{th} potential candidate for the j^{th} business process.

The partner selection problem is to select at least one but no more than two candidates from the u_i^j for each business process so that the resultant combination minimizes three objective functions:

1. The running cost (the cost of the alliance operation): it consists of the internal cost of each candidate (when is chosen individual) and the partnership link-cost (the link-cost between any two candidates):

$$\min C = \min \left\{ \sum_{j=1}^J \sum_{i=1}^{I_j} H_i^j C_i^j + \frac{1}{2} \sum_{j'=1}^J \sum_{i'=1}^{I_{j'}} \sum_{j''=1}^J \sum_{i''=1}^{I_{j''}} H_{i'}^{j'} H_{i''}^{j''} C_{i'i''}^{j'j''} \right\} \quad (1)$$

where:

$$H_i^j = \begin{cases} 1, & \text{if } u_i^j \text{ is selected} \\ 0, & \text{if } u_i^j \text{ is not selected} \end{cases} \quad (2)$$

C_i^j is the internal cost for choosing u_i^j ; $C_{i'i''}^{j'j''}$ is the linked cost between $u_{i'}^{j'}$ and $u_{i''}^{j''}$; $i', i'' \in [1, I]$ and $j', j'' \in [1, J]$

2. The reaction time to the market: it consists of the internal reaction time of each candidate and the link time between any two candidates:

$$\min T = \min \left\{ \sum_{j=1}^J \sum_{i=1}^{I_j} H_i^j T_i^j + \frac{1}{2} \sum_{j'=1}^J \sum_{i'=1}^{I_{j'}} \sum_{j''=1}^J \sum_{i''=1}^{I_{j''}} H_{i'}^{j'} H_{i''}^{j''} T_{i'i''}^{j'j''} \right\} \quad (3)$$

where: T_i^j is the reaction time for choosing u_i^j ; $T_{i'i''}^{j'j''}$ is the link time between any two candidates $u_{i'}^{j'}$ and $u_{i''}^{j''}$, $i', i'' \in [1, I]$ and $j', j'' \in [1, J]$

3. The running risk of enterprise operation

$$\min R = \min \sum_{j=1}^J \max_{i \in [1, I_j]} H_i^j R_i^j \quad (4)$$

where: R_i^j is the risk for choosing u_i^j

The total objective function combines the three objectives (running cost, reaction time and running risk) into a single objective function by using a weighted sum:

$$\begin{aligned} \min F(x) = & w_1 \left\{ \sum_{j=1}^J \sum_{i=1}^I H_i^j C_i^j + \frac{1}{2} \sum_{j=1}^J \sum_{i=1}^I \sum_{i'=1}^I \sum_{i''=1}^I H_i^{j'} H_{i'}^{j''} C_{i''}^{j''} \right\} + w_2 \left\{ \sum_{j=1}^J \sum_{i=1}^I H_i^j T_i^j + \frac{1}{2} \sum_{j=1}^J \sum_{i=1}^I \sum_{i'=1}^I \sum_{i''=1}^I H_i^{j'} H_{i'}^{j''} T_{i''}^{j''} \right\} + \\ & + w_3 \sum_{j=1}^J \max_{i \in [1, I]} H_i^j R_i^j \end{aligned} \quad (5)$$

where the criteria weights w_1 , w_2 , and w_3 acquire the relative importance of the decision criteria.

If we assume that only one candidate can be selected for a business process, then the number of feasible solutions of the problem is $\prod_{j=1}^J I_j$. If two candidates can be selected,

the number of feasible solutions of the problem is $\frac{1}{2^J} \prod_{j=1}^J I_j (I_j + 1)$.

As one can see, the problem size grows with the sub-project number very rapidly. Even for a small scale problem, there is huge possibility of combination output, so it is hard to deal with it by a simple enumeration method. More, because of the high computational complexity, conventional optimization methods seems not appropriate for this class of multiobjective nonlinear optimization problems.

The proposed approach

In this study, a random-weighted GA -RWGA (Murata et al., 1996) based on binary encoding is proposed. A normalized vector $w_i = (w_1, w_2, w_3)$ is randomly generated for each solution $x_i \in P^{(0)}$ during the selection phase at each generation. By changing weights during the running time, this approach provides multiple search directions and thus an increased ability to evaluate the area uniformly over the entire frontier.

This procedure applied in our study is given as follows:

Step1(Initialization): The GA begins with generating a random initial population $P^{(0)}$ of candidate solutions. Set $t=0$.

Step2(Evaluation): Assign a fitness value to each solution $x_i \in P^{(0)}$ by performing the follow steps:

i. Generate the weights as follows:

$$w_1(t) = \frac{1}{2} \left| \sin\left(\frac{2\pi}{G_{MAX}}\right) + \cos\left(\frac{2\pi}{G_{MAX}}\right) \right| \quad w_2(t) = [\text{rand}] (1 - w_1(t)) \quad w_3(t) = 1 - (w_1(t) + w_2(t)) \quad (6)$$

where t =number of generation, $t=1,2,\dots$, G_{MAX} . G_{MAX} is the maximum number of generations.

ii. Calculate: objective function from equation (5)

Step 3 (Selection): Minimizing F is based on finding a maximum fitness value in the searching process:

$$f_i = \text{fitness}(x_i) = \frac{F(x_i)}{f^{\max}(x_i)}, \quad (7)$$

$$f^{\max}(x_i) = \{ \max F(x_i) \mid x_i \in P^{(t)} \} \quad (8)$$

Calculate the selection probability of each solution $x_i \in P^{(t)}$:

$$p_i = \frac{f_i - f^{\min}}{\sum_{j=1}^{PS} (f_j - f^{\min})} \quad (9)$$

Where: PS is the population size

$$f^{\min} = \{ \min F(x) \mid x \in P^{(t)} \} \quad (10)$$

Select parents using the fitness-proportion selection based on probabilities calculated in (9).

Step 4 (Genetic operators): Thereafter crossover and mutation operators are applied on the population.

Step 5: If the stopping condition is satisfied, return $P^{(t)}$. Otherwise set $t = t+1$ and go to Step 2.

Mapping of the problem

A population of constant size PS consisting of binary chromosomes is given by:

$$P_k^{\text{gen}} = [(u_1^1, u_2^1, \dots, u_{I_1}^1), \dots, (u_1^k, u_2^k, \dots, u_{I_k}^k), \dots, (u_1^J, u_2^J, \dots, u_{I_J}^J)] \quad (11)$$

sub-project 1 sub-project k sub-project J

$$\text{subject to: } \sum_{i=1}^{I_k} u_i^k \geq 1 \quad (12)$$

$$\text{where } u_i^j = \begin{cases} 1, & \text{if the } i^{\text{th}} \text{ candidate is selected in sub-project } j \\ 0, & \text{if the } i^{\text{th}} \text{ candidate is not selected} \end{cases} \quad (13)$$

$k=1, \dots, PS$; $\text{gen}=1, \dots, G_{\text{MAX}}$; PS is the population size;

G_{MAX} is the maximum number of generations (first we set $G_{\text{MAX}}=100$).

The initial population is randomly generated in accordance with (11), (12) and (13).

Once the individuals of current population are evaluated according to their fitness, the individuals that will be the parents of the next generation are selected according to the desired selection scheme. This study uses the proportional (roulette wheel) selection. Next, the selected individuals are paired off randomly to give rise to new offsprings.

In order to develop an algorithm with a high level of performance, new enhancements were proposed. The reproduction of the individuals in this study is inspired by the organic mechanism of a meiotic cell division (Dinu et al., 2010).

FIGURE 1. THE PROPOSED GA FOR THE PROBLEM

```

begin
  t:= 0;
  initialize population  $P^{(0)}$  randomly;
  evaluate  $P^{(0)}$ 
  while t ≤ Gmax
    //roulette wheel selection
    for all member of population
      r:=random[0,1]; k:=0; partial_sum:=0
      repeat
        k:=k+1;
        partial_sum:=partial_sum +fitness(k);
        until( $r < \frac{\text{partial\_sum}}{\sum_k \text{fitness}(k)}$  or new population is full)
      select_individual:=k
    repeat
    //meiosis
    for all member of population
      //replicate_chromosome1
      chromatid1:=chromosome1; chromatid2:=chromatid1
      //replicate_chromosome2
      chromatid3:=chromosome2;
      chromatid4:=chromatid3
      //forming gamete1, gamete2
      //crossover(chromatid1, chromatid3)
      r:=random(0,1)
      gamete1:=r*chromatid1+(1-r)*chromatid3
      gamete2:= (1-r)*chromatid1+r*chromatid3
      //forming gamete3, gamete4
      //crossover(chromatid2, chromatid4)
      r:=random(0,1)
      gamete3:=r*chromatid2+(1-r)*chromatid4
      gamete4:= (1-r)*chromatid2+r*chromatid4
    //fertilization
    generate from gametes by randomly selection:
    offspring1
    offspring2
    // mutation
    i:=random {1,2,...,  $\sum_{j=1}^J I_j$  }
    if ( $p_{\text{mut}} > r^{\left(1 - \frac{\text{gen}}{G_{\text{max}}}\right)}$ )
      offspring1[i] → offspring1mut[i]
      offspring2[i] → offspring2mut[i]
    endif
    repeat
    evaluate  $P^{(t+1)}$ 
  repeat
end

```

In this context, the term “meiosis” refers to the process whereby a nucleus divides by two divisions (meiosis I and meiosis II) into four gametes. Meiosis halves the number of chromosomes before sexual reproduction, thereby ensuring that chromosome number does not double with each generation.

Before meiosis, each chromosome is replicated, forming two sisters “chromatids” that remain linked together. The two sister chromatids forming each homolog are then separated during the second meiotic division. The implemented crossover is arithmetic crossover. The probability of crossover is p_c , so that an average of $p_c \times 100\%$ chromosomes undergoes crossover. Fertilization (putting together two gametes resulted from meiosis) is done by randomly combining gametes from the gene pool: two of the gametes from the four that have been formed are then selected randomly to form two new offsprings.

During the selection, crossover and mutation stages, if the generated individual does not satisfy the constraint (12), it will not be considered and the process will continue until the new individual satisfies the constraint.

The scheme of the designed Genetic Algorithm for this problem is given in Figure 1:

The next genetic operator, mutation, introduces a random bit value change in chromosome with a small probability. Randomly chosen string positions change from 0 to 1 and vice versa to enlarge the information contained in the population. This adds a random search character to the GA.

We propose a mutation operator with step-size adaptation defined as follows:

if $P_k^{\text{gen}} = [(u_1^1, u_2^1, \dots, u_{l_1}^1), \dots, (u_1^k, u_2^k, \dots, u_{l_k}^k), \dots, (u_1^J, u_2^J, \dots, u_{l_J}^J)]$ and u_i^k is selected at random for mutation then a new offspring is generated only if :

$$p_{\text{mut}} > r^{(1 - \frac{\text{gen}}{G_{\text{max}}})^\tau} \quad (14)$$

As can be seen from (14), the number of changes decreases as one approach the maximum number of generations. Thus, this mutation operator performs global search during the initial generations and local search in the later generations. Moreover, the local searching ability of the algorithm is improved, as well as the algorithm's efficiency. For this mutation operator we have set the mutation rate at 0.03.

Case study of a partner selection scenario

For validation, supposing core competencies required by a VE can be decomposed in 5 business processes (sub-projects): Research, Design, Purchase, Manufacture and Sale and the number of candidate partners they contain is 2, 3, 4, 3, and 2 labeled as $R_1, R_2, D_1, D_2, D_3, P_1, P_2, P_3, P_4, M_1, M_2, M_3, S_1, S_2$. Altogether, there are 14 binary bits in each chromosome.

Data obtained from bidding are shown in Table1 and Table 2.

With this data, the problem is that of selecting the best partner for each sub-project, with respect to minimizing cost, time and risk.

The optimum global fitness is found to be 0.8247 and the optimal solution is [01001100011001]. This means the best selection is $R_2, D_3, P_1, M_1, M_2, S_2$. It was obtained for the GA parameters set at the values:

- Size of population PS: 100
- crossover rate $p_c=0.8$
- total number of generations $G_{\text{MAX}}=100$

TABLE 1. INTERNAL COST, INTERNAL REACTION TIME AND RUNNING RISK OF EACH CANDIDATE PARTNER

Partners	Internal cost C_i (M. U.)	Internal reaction time T_i (weeks)	Running risk R_i
R ₁	59.2	5	0.3
R ₂	81.4	11	0.2
D ₁	97.16	12.5	0.5
D ₂	81.04	8	0.6
D ₃	73.48	10.5	0.4
P ₁	52.08	7	0.2
P ₂	104.26	6.5	0.4
P ₃	83.14	4	0.7
P ₄	92.11	7	0.5
M ₁	54.16	9.5	0.3
M ₂	68.24	8	0.1
M ₃	83.28	3.5	0.6
S ₁	67.54	6	0.2
S ₂	101.92	9	0.8

TABLE 2. LINK COST AND LINK TIME BETWEEN ANY TWO CANDIDATES

	R ₁	R ₂	D ₁	D ₂	D ₃	P ₁	P ₂	P ₃	P ₄	M ₁	M ₂	M ₃	S ₁	S ₂
R ₁	0	8.9	11.8	7.5	12.3	5.9	4.8	12.4	7.2	8.3	5.7	6.2	10.7	5.4
	0	1.5	2	3.5	1.5	2.5	0.5	3	2.5	1	1.5	2	4	3.5
R ₂	8.9	0	12.4	4.9	7.2	5.8	3.7	5.6	4.9	7.3	5.8	11.6	8.1	7.2
	1.5	0	3	4.5	2	1	2.5	2	3	1.5	3.5	4	2.5	2
D ₁	11.8	12.4	0	8.5	2.9	8.4	7.3	6.4	5.9	7.5	6.3	8.4	5.9	6.8
	2	3	0	4.5	3.5	4	4.5	2.5	3	2	2.5	3	1.5	2.5
D ₂	7.5	4.9	8.5	0	5.9	8.2	11.3	8.2	9.5	7.3	8.4	3.8	5.6	8.1
	3.5	4.5	4.5	0	3	4	1.5	2	2.5	4.5	3	4	2.5	2
D ₃	12.3	7.2	2.9	5.9	0	4.6	8.2	10.1	8.9	4.1	7.5	6.3	5.6	8.1
	1.5	2	3.5	3	0	2.5	1.5	2.5	1	2	2.5	4	1.5	2.5
P ₁	5.9	5.8	8.4	8.2	4.6	0	10.5	8.6	9.3	10.2	4.6	8.3	6.9	8.4
	2.5	1	4	4	2.5	0	4	3.5	1	2	2.5	1.5	4	3.5
P ₂	4.8	3.7	7.3	11.3	8.2	10.5	0	9.8	7.3	6.2	5.1	4.9	7.5	6.3
	0.5	2.5	4.5	1.5	1.5	4	0	2.5	3	1.5	3.5	1.5	2.5	3
P ₃	12.4	5.6	6.4	8.2	10.1	8.6	9.8	0	9.2	5.9	8.3	6.4	7.5	4.8
	3	2	2.5	2	2.5	3.5	2.5	0	2.5	1.5	1	3	1.5	2
P ₄	7.2	4.9	5.9	9.5	8.9	9.3	7.3	9.2	0	8.9	7.2	5.6	7.1	8.5
	2.5	3	3	2.5	1	1	3	2.5	0	2.5	1.5	2	3	3.5
M ₁	8.3	7.3	7.5	7.3	4.1	10.2	6.2	5.9	8.9	0	6.9	8.2	6.3	7.4
	1	1.5	2	4.5	2	2	1.5	1.5	2.5	0	1.5	1	2	1.5
M ₂	5.7	5.8	6.3	8.4	7.5	4.6	5.1	8.3	7.2	6.9	0	7.4	8.1	6.9
	1.5	3.5	2.5	3	2.5	2.5	3.5	1	1.5	1.5	0	2	2.5	1
M ₃	6.2	11.6	8.4	3.8	6.3	8.3	4.9	6.4	5.6	8.2	7.4	0	7.5	3.9
	2	4	3	4	4	1.5	1.5	3	2	1	2	0	2	2.5
S ₁	10.7	8.1	5.9	5.6	5.6	6.9	7.5	7.5	7.1	6.3	8.1	7.5	0	6.9
	4	2.5	1.5	2.5	1.5	4	2.5	1.5	3	2	2.5	2	0	2.5
S ₂	5.4	7.2	6.8	8.1	8.1	8.4	6.3	6.3	8.5	7.4	6.9	3.9	6.9	0
	3.5	2	2.5	2	2.5	3.5	3	3	3.5	1.5	1	2.5	2.5	0

GA parameters were selected following parameter sensitivity analysis.

The generation process is shown in Figure 2. From this figure one can observe an intense increase in early generations, where individuals are far from the optimum. The algorithm finds an optimal solution within less than 100 generations; that leads to less computational time for the solution process.

FIGURE 2. THE CONVERGENCE OF THE PROPOSED ALGORITHM

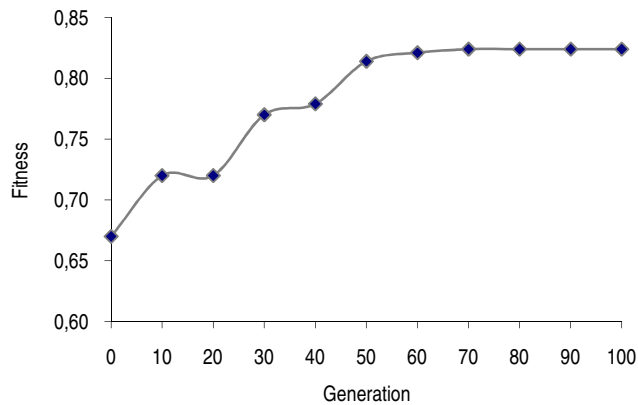
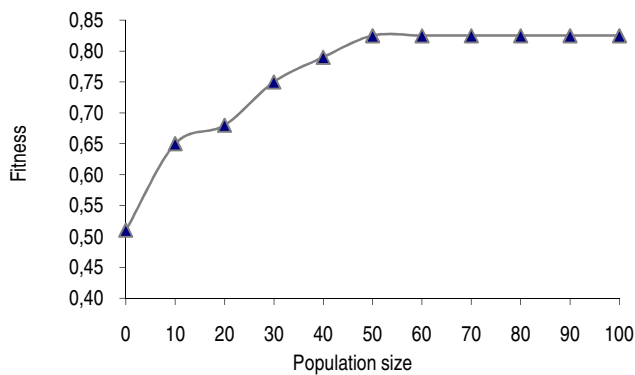


FIGURE 3. THE OPTIMUM GLOBAL FITNESS FOR DIFFERENT POPULATION SIZE



The sensitivity analysis was performed on GA parameters to determine their influence on the algorithm's performance. First, analysis was performed for 10 values of population size (PS) in the range [10, 100] with an increment of 10, while the value for crossover was set at 0.7, in accordance with previous results in GA applications. The results obtained after performing 50 independent runs for each case (Figure 3) indicate that the performance of the algorithm was improved when the population size increased from 10

to 50, but no significant improvements were observed when the population was further increased.

Maintaining the obtained population of 50, the crossover rate was changed from 0.5 to 0.9 with an increment of 0.01 and 50 independent tests were performed for each case. The obtained results are shown in Figure 4. The best option for crossover rate is located at 0.8. After this value, the performance decreases with the increase in crossover rate.

FIGURE 4. THE OPTIMUM GLOBAL FITNESS FOR DIFFERENT CROSSOVER RATE

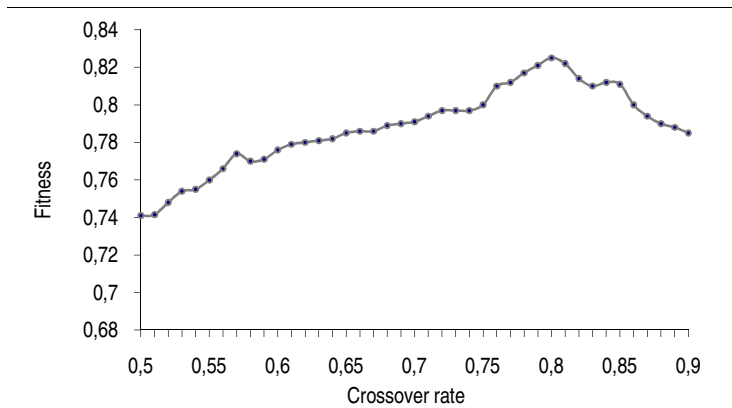
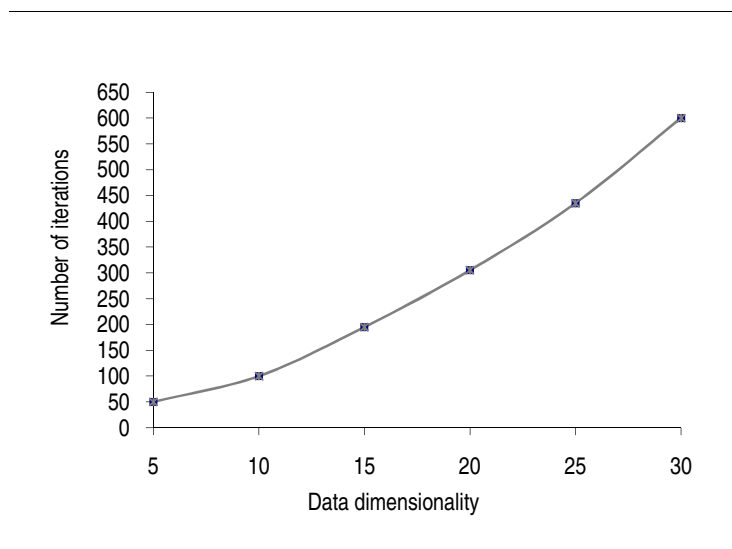


FIGURE 5. THE SCALABILITY OF THE PROPOSED ALGORITHM ON LARGE DATA SETS



The scalability of the proposed algorithm on large data sets

In order to investigate the scalability of the algorithm when the dimensionality of the problem is increased, different large test cases are randomly generated by changing the number of business processes from 10 to 30 with an increment of 5. The number of candidate partners for each sub-project was set at 5. The GA parameters remained the same as that of previous experiment, excepting G_{MAX} . Figure 5 and Table 3 summarizes how the scalability of the algorithm is influenced over high dimensional optimization problems. Each graph's point was plotted when the convergence of the solution was observed.

TABLE 3. NUMBER OF ITERATIONS REQUIRED FOR LARGE TEST CASES

Number of business processes	5	10	15	20	25	30
Problem size	7.6×10^5	5.7×10^{11}	4.4×10^{17}	3.3×10^{23}	2.5×10^{29}	1.9×10^{35}
Number of iterations required	55	100	195	305	435	600

As one can see, while the search space increases extremely rapidly when number of sub-projects increases, the computational complexity increases only marginally worse than linearly.

Conclusion

As described in this paper, selecting the best candidate enterprise portfolio represents a critical issue in developing successful alliances. Partner selection is a multiobjective non-linear optimization problem which is not easy to solve optimal.

Although there are many factors that influence partner selection, minimizing cost, time and risk are critical to ensure the success of the virtual enterprise. As a result, this study proposes a design selection model based on an improved adaptive GA. The addition of the proposed meiosis specific features and random-generated weights results in better robustness and convergence stability. The proposed mutation operator with step-size adaptation performs strong exploration initially and exploitation in later generations. This allows a faster convergence and also avoids premature convergence.

On the basis of the numerical investigations, the incorporation of the proposed enhancements has been successfully proved.

In order to develop the research, we intend to consider further study concerning the analysis for other existing selection, crossover and mutation operators. We also plan to investigate more practical and complicated problems in a more realistic environment.

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