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A SIMULATION-OPTIMIZATION APPROACH USING GENETIC SEARCH FOR SUPPLIER SELECTION

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ABSTRACT

The paper presents a simulation-optimization approach using genetic algorithm to the supplier selection problem. The problem consists in selecting a portfolio of suppliers from a set of pre-selected candidates. The supplier selection is a multi-criteria problem that includes both qualitative and quantitative criteria. In order to select the best suppliers it is crucial to make a trade off between these tangible and intangible criteria, some of which may be contradictory. The proposed approach uses discrete-event simulation for performance evaluation of a supplier portfolio and a genetic algorithm for optimum portfolio identification based on performance indices estimated by the simulation. Numerical results on a real-life case study are presented.

1 INTRODUCTION

The global economy is forcing companies to take almost everything into consideration at the same time. Increasing flexibility is needed to remain competitive and responsive to rapidly changing markets. There is no generally accepted method by managers and researchers for designing a global supply chain.

Strategic sourcing (SS) is one of the most important business functions and has been one of the fastest growing areas of industrial management, particularly over the last ten years. Under the expanded heading of logistics it is now an integral part of the company strategy covering the purchasing activity. As technological complexity increased, supplier selection has become more dynamic and complex to analyze and to solve.

Purchasing costs of raw materials and components from external suppliers, are very important. In automotive industries, these costs may be more than 50% of revenues. That can go up to 80% of the total product costs for high-technology firms (Weber *et al.* 1991). Therefore, companies are interested by the following question: How to provide the desired products and/or services to customers faster, cheaper, and better than the competition? Managers come to realize that they cannot do it alone; rather, they must work on a cooperative basis with the best organizations in their logistic systems including suppliers, plants, warehouses, distribution centers and customers, in order to succeed. Without any doubt, supplier selection is one of the decisions which determine the long-term viability of the company (Thompson 1990).

The search for new suppliers is a continuous priority for companies in order to upgrade the variety and typology of there products range. This is essentially due to two reasons. First, product life cycle is becoming very short (3 to 4 years or less) and new models must often be developed by using completely renewed material or with new technologies. Second, many industries are labor intensive. These aspects are expressed through a complex pattern of demand for material and labor. Two different aspects characterize the supplier selection problem:

1. The first aspect is the determination of the number of the suppliers and modes of relations with them. Considering the characteristics of the company, product and market, company's strategy can encourage a large number of suppliers or not. On the other hand, the company can have a hierarchical relation and a significant number of suppliers for the standard parts in order to establish a competition between them and thus to reduce purchasing costs. Several authors (Kamath *et al.* 1994), (Bensaou 1999) and (D'Amours *et al.* 2001) are interested by the suppliers classification problem.
2. The second aspect is related to the selection of the best suppliers among the existing criteria.

In this work, we consider the selection of suppliers among some predetermined ones. The objective of our work is to propose a simulation-optimization approach using a genetic algorithm to efficiently solve the supplier selection problem. In this approach, the genetic algorithm, based on a fitness function, provides possible configurations of the selected suppliers, including transportation links. An evaluation of each configuration based on some performance indicators (ex. total backlogging cost, total transportation and purchasing costs, inventory cost, average lead-time…) is given by the simulator.

The following sections describe in details the proposed approach. A real life case study is presented and simulation results are given for the validation of our approach.

2 LITERATURE REVIEW

Supplier selection decisions are complicated by the fact that various criteria must be considered in decisions making process. The analysis of such criteria and measuring the performances of suppliers have been the focus of many scientists and purchasing practitioners since the 1960's. Many papers and researches were dedicated to this problem. This section briefly summarizes the literature of existing approaches and results obtained for the supplier selection problem.

An interesting work, which is a reference for the majority of papers dealing with supplier or vendor selection problem, was presented by Dickson (Dickson 1966). Dickson's study was based on a questionnaire sent to 273 purchasing agents and managers selected from the membership list of the National Association of Purchasing Managers. 23 criteria were ranked with respect to their importance observed in the beginning of the sixties. At that time, the most significant criteria were "quality" of the product, "on-time delivery", "performance history" of the supplier and the warranty policy used by the supplier.

In (Weber *et al.* 1991) a classification of all the published papers (since 1966), according to the studied criteria, is presented. The result, based on 74 papers, shows that "Price", "Delivery", "Quality" and "Production capacity and location" are the criteria most often treated in the literature. Overall, the 23 criteria presented by Dickson still cover the majority of the criteria presented in the literature until today. On the other hand the evolution of the industrial environment modified the degrees of the relative importance of these criteria.

Ellram (1990) proposes three principal criteria which are: 1) the financial statement of the supplier, 2) the organizational culture and strategy of the supplier, and 3) the technological state of the supplier. For each one of these three criteria, the author presents several sub-criteria. In (Barbarosoglu and Yazgac 1997), authors distinguish three principal criteria: 1) the performance of the supplier, 2) technical capability and financial of the supplier, 3) the quality system of the supplier, and propose some sub-criteria like in (Ellram 1990).

To solve the supplier selection problem, existing methods, can be classified in three principal categories. A method can of course be the combination of the elementary methods presented below.

1. Elimination methods (Crow *et al.* 1980, Wright 1975).
2. Optimization methods.
   - Without constraints: AHP approach 'Analytical Hierarchic Process' (Golden *et al.* 1989).
   - Subject to a set of constraints: mathematical programming approach (Weber *et al.* 1991, Weber and Current 1993, Ghodsypour and O'Brien 1998).
3. Probabilistic methods (Soukup 1987).

Table 1 summarizes advantages and disadvantages of existing selection methods. Note that most existingapproaches do not take into account the dynamic interaction

Table 1: Advantages and Disadvantages of Different Selection Methods

Method			Advantages	Disadvantages
Elimination			- Fast - Simple to use - Take into account subjective criteria	- The final choice is not made starting from the total performance on all the criteria - No possibility to introduce constraints in the model
Optimization	Without constraints	Multi-criteria	- Simple to use -Take into account all criterion types (subjective and objective)	- Depends on the human judgment - No possibility to introduce constraints in the model
		Oriented cost	Objective method	- Does not take into account the subjective criteria
	Subject to constraints	Single criterion	- Proposes an optimal solution - Possibility to introduce several types of constraints	- Does not take into account the subjective criteria - Not clear for the manager
		Multi-criteria	- More than one optimal solution - Possibility to introduce several types of constraints	- Difficult to take into account subjective criteria - Not clear for the manager to analyze
Probabilistic			Analyze the uncertain behavior of suppliers	- No optimal solution - Not easy to analyze - No possibility to introduce constraints in the model

between the suppliers and the focal enterprise and, as are-sult, the models of key performance criteria are most often over-simplified. By combining simulation and optimization, the approach proposed in this paper allows realistic modeling of key performance criteria.

3 GENETIC ALGORITHMS

The literature on genetic algorithms is very rich. Many researches dealing with this class of methods are presented since the work of Holland (1975). There are many variations, but in this section, one present briefly the definition and concepts of a basic genetic algorithm.

Genetic Algorithm (GA) is a search algorithm based on the mechanism of natural selection and natural genetics and is used to search large, non-linear search spaces where expert knowledge is lacking or difficult to encode and where traditional optimization techniques fall short (Goldberg 1989).

The basic principles of GA's were firstly designed by Holland (1975). A GA works with a population of individual strings (chromosomes), each representing a possible solution to a given problem. In this work each position in the chromosome may take on one of a finite set of values, and represents a variable from the user's system. Each chromosome (individual) is assigned a fitness value according to the result of the fitness (or objective) function. Such highly fit chromosomes will survive more frequently than other in the population, and they are given more opportunities to reproduce and the offspring (child) share features taken from their parents. For many problems (manufacturing, communication, neural networks, etc…) genetic algorithms can often find good solutions (near-optimal) in around 100 generations. This can be many times faster than an exhaustive search approaches.

GAs judiciously use the idea of randomness when performing a search. However, it is important to state that genetic algorithm is *not* a simply random search algorithm. Indeed, random search algorithms can be inherently inefficient due to the directionless nature of their search. GAs are not directionless. They utilize knowledge from previous generations in order to construct a new generation that will approach the optimal solution. In other words, they use past knowledge to direct the search.

3.1 GA Operators

Three basic operations that characterize GAs are respectively: selection, crossover and mutation. Suppose *P(t)* is the population of chromosomes at generation *t*, the structure of a simple GA for a particular application consists of the following principal phases (see Goldberg 1989 for more details).

```
SimpleGeneticAlgorithm ( )
{   t=0
    Initialize Population P(t);
    Evaluate P(t)  (Calculate Fitness Function);
    While (termination condition false) do
        {Applied the following procedures to P(t)
            1. Select P(t+1) from P(t),
            2. Crossover (recombine P(t+1));
            3. Mutation (recombine P(t+1));
            4. Evaluate P(t+1);
        t=t+1;
        }
}
```

Initialization: The algorithm starts with a set of solutions (represented by chromosomes) called population. Each chromosome represents a possible solution to the problem. The most-used way (though not the only way) of encoding chromosomes is a binary string.

Calculation of Fitness Function: An evaluation function, called fitness function needs to be defined for a problem to be solved in order to evaluate chromosomes. A chromosome with a high fitness value is likely to be a good solution to the problem.

Selection of the Best Individual: Selection is a process in which chromosomes are copied according to their fitness function value. There are many methods for selecting the best chromosome – such as: Roulette Wheel Selection, Boltzmann Selection, Tournament Selection, Rank Selection, Steady-State Selection and so on.

Crossover: The traditional crossover operator randomly by selecting genes from parent chromosomes creates new chromosomes (individuals). Chromosomes of the two parents are split into two (equal or unequal) halves each. Both the chromosomes are cut similarly. The halves are interchanged and combined to form the child chromosome.

Mutation: After a crossover is performed, the resulting solution might fall into a local optimum - hence some genes from parent chromosome are randomly changed to provide a new child. The traditional mutation operator occurs according to some user-defined probability (usually between 1% and 5%), randomly chooses a gene and changes it from 1 to 0 or from 0 to 1.

Important: However, when creating a new population by crossover and mutation, the best chromosome might be lost. Hence, Elitism is a method which first copies the best chromosome(s) to the new population (from P(t) to P(t+1)), and this before the crossover and mutation application. Elitism rapidly increases the performance of the GA, by preventing loss of the best-found solution. The Elitism method is used in this comprehensive simulation-optimization framework for supply chain network design.

3.2 Motivation for Using GA

Remember that our objective is to develop a simulation-optimization approach for the supplier selection problem with realistic performance criteria models.

Many approaches and methods (ex. elimination, AHP, mathematical programming…) were proposed and applied to the supplier selection problem. Why not use one of them for simulation modeling? To answer the previous question, let us first analyze main complicating factors of the supplier selection problem.

- The strategic nature of the decisions "Selecting capable suppliers is one of a purchasing manager's most important responsibilities" (Dobe et *al.*, 1984).
- The intervention of various services of the company (Dyer and Forman 1992) and (Mobolurin, 1995). Indeed, this (these) decision (s) will be reflected on several services of the company, like production, transportation, storage, purchase, etc.
- The multi-criteria nature, which includes both qualitative and quantitative some of which may conflict. Select the supplier(s) consists in making the best compromise between the criteria.
- Comparing to the criteria, problem parameters and market behaviors are mostly uncertain. The intervention of various industrial and social constraints related to customers and suppliers, such as limited capacity of the supplier, minimum and maximum order quantity accepted by suppliers, quality, delivery time and price, complicate the development of an efficient approach.
- Uncertainty on market behavior and product life cycle (short).

The Differences between Genetic Algorithms and Traditional Methods are mainly:

Genetic algorithms use an encoding of the control variables, rather than the variables themselves. For example, if one wants to select the supplier who provide the raw materials faster and cheaper, the GA would not deal directly with lead-time and/or costs values, but with chromosomes that encode decisions related to the selection or not of such supplier and the corresponding percentage of assigned demand, when more than one supplier are selected. Each chromosome corresponds to a possible configuration of the selection.

Genetic algorithms search from one population of solutions to another, rather than from individual to individual. This gives GAs the power to search noisy spaces littered with local optimum. Instead of relying on a single configuration to search through the space, the GAs look at many different areas of the solution space at once, and uses this information to guide it.

Genetic algorithms use only objective function information to guide themselves through the solution space, not derivatives. Many search techniques need a variety of information to guide themselves (ex. mathematical programming). The only information a GA needs is some measure of fitness about a configuration in the space of solutions (sometimes known as an objective function value). Once the GA knows the current measure of "goodness" about a configuration, it can use this to continue searching for the optimum.

GAs are probabilistic in nature, not deterministic. This is a direct result of the randomization techniques used by GAs. This is not the case of most existing methods.

One of the most attractive advantages of using GAs as design tools is their ability to find solutions to problems in a way completely free of preconceptions about what is possible and what is not. This is something that human designers find very difficult.

4 STRUCTURE OF THE SIMULATION-OPTIMIZATION MODEL

This section describes the structure of the simulation-optimization model (Figure 1) in detail.

The model is mainly composed of three parts: a GA optimizer, a supply chain simulator and a simulation model generator. For each iteration, the GA optimizer proposes certain network configuration, supplier portfolio in this case. Starting from the output given by the optimizer, the model generator generates corresponding supply chain simulation model. Subsequently, necessary properties of candidate suppliers are provided as input of the simulator and the simulation is performed to evaluate relevant Key Performance Indicators (KPIs) of the candidate supply portfolio. More specifically, discrete-event simulation is employed in the simulator, with which the fitness of each candidate supply portfolio is evaluated. Inputs for the simulator include demand pattern, inventory control policy, supplier characteristics and information related to transportation links. Fitness of the configuration is calculated based on the estimated KPIs.

As a preliminary simulation-optimization approach, this model only focuses on strategic decisions of supplier selection. Operation rules, such as orders assignment, are not taken into consideration by the optimization part. Instead, relevant assumptions are introduced when building the simulation model.

Main processes and assumptions of the simulation model are listed as follows:

1. Customers generate demands for final products.
2. Those demands are collected by the focal enterprise and then forwarded to a warehouse. According to the on-hand inventory level, demands are fulfilled immediately or backlogged.

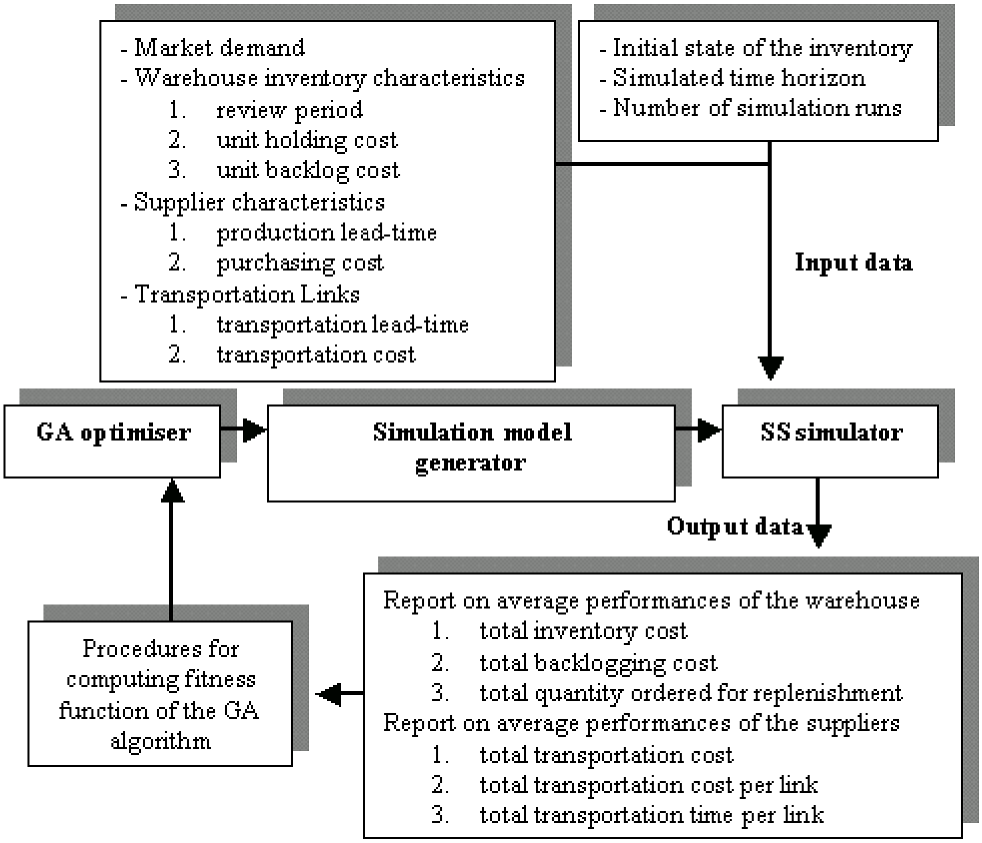

Figure 1: Structure of the Simulation-Optimization Model

3. (s, S) policy is employed at the warehouse to control the inventory, and its position is reviewed periodically. If the inventory position is shorter than "s", an order is generated and collected by the enterprise.
4. The focal enterprise makes the decision to assign orders to its suppliers with respect the order assignment rules.
5. After a certain period, namely supply lead-time, the products are delivered to the warehouse and the inventory is replenished.

Several KPIs are considered for the performance evaluation of different supply portfolios. Total purchasing costs, transportation costs and inventory costs are key criteria for supplier selection from the quantitative point of view. The total backlogged demand is also calculated and emphasized as an important indicator of customer service level.

5 A REAL LIFE CASE STUDY

The real life case study presented in this paper is a part of a supply chain for "Classic" boots distributed by a textile enterprise located in Europe. The overall objective is to redesign the supply chain, mainly by selecting new suppliers for the products, and evaluate different solutions in term of overall costs, robustness to changes in product demand, environmental and social impacts and sensitivity to changes to warehouses policies.

For the actual situation, the product is made in an unique plant in country V (Supplier A). Boots are then collected in containers and transported by boat from harbor H to harbor G (no transportation is considered between Supplier A and harbor H). After that, they are transported by road from harbor G to the central warehouse of the enterprise, where they are stored. The product is then distributed to the retailers along with other products. See Figure 2 for a simple representation of the actual supply chain.

Figure 2: Actual Situation

The overall objective of the case study is to consider the introduction of one or more new suppliers (i.e. other production plants located in different countries), denoted respectively Supplier B, Supplier C and Supplier D, that can support or substitute the actual one (Supplier A). This will, of course, need the redesign of the overall supply chain network for the enterprise.

The redesign needs the comparison of different configurations of the supply chain, by considering the introduction of one or more of the following suppliers:

- The actual supplier (Supplier A located in Far East)
- A new supplier in Far East (Supplier B)
- A new supplier in East Europe (Supplier C)
- A new supplier in the same country as the central warehouse of the enterprise (Supplier D)

Figure 3 presents the potential suppliers and their corresponding transportation modes to select.

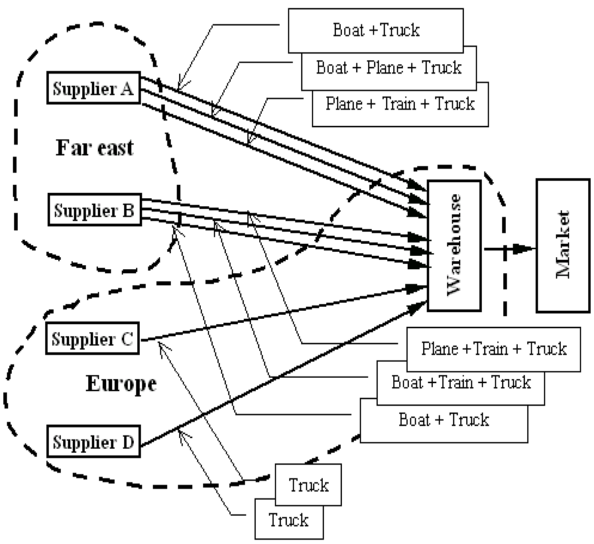

Figure 3: Potential Suppliers and Transportation Modes

From each supplier until the enterprise warehouse different transportation links are considered. They are summarized as follows:

1. Transportation from Far East to Europe (required for suppliers A and B).
   - Transportation by boat from delivery point to harbor G.
   - Transportation by boat from delivery point to harbor R.
   - Transportation by plane from delivery point to airport I.
   - Transportation by boat from delivery point to harbor D and by plane from harbor D to airport I.
2. Transportation within Europe (required for all the suppliers).
   - Transportation by road from harbor G, harbor R, airport I or Supplier D to the central warehouse of the enterprise.
   - Transportation by train + road from harbor G, harbor R, airport I or Supplier D to the central warehouse of the enterprise.

6 EXPERIMENTAL RESULTS

To test the performance of the proposed simulation-optimization method, a simulation-optimization model is built to study the foregoing supply selection case.

We use a binary string to represent the portfolio of different suppliers, where "1" means the corresponding supplier is included in the supply portfolio and "0" means the supplier is excluded from the supply portfolio. Each population contains 20 individuals. A chromosome is composed of 8 genes, where each gene represents a supplier and its corresponding transportation link. Indeed, we have 4 potential suppliers A, B, C and D with respectively 3, 3, 1 and 1 potential transportation links (see figure 3). Moreover, roulette wheel selection is used to select chromosomes for the two-point crossover. The probability of crossover operation is set as 0.9. Mutation is performed immediately after the crossover with probability 0.001. To balance the disruptive nature of the chosen crossover and mutation, we use the *Elitist* strategy to preserve the best individuals. And we run the GA for 150 generations.

Given the candidate supplier portfolio, the model generator generates a corresponding discrete-event simulation model for fitness evaluation. The simulation horizon is set to 2 years since supply selection is a typical strategic decision. Considering that GA needs tens of thousands of simulations to search the solution space, we implement the simulation model in an aggregated way. Actually a single simulation run takes around 1.2 second.

In this paper, order assignment follows a simple rule: each order is divided by the number of available suppliers and subsequently each sub-order is forwarded to an active supplier. Thus, the complete solution space consists of 253 supply portfolios. The number 253 comes from $\sum_{i=1}^{8} C_8^i$, representing the sum of different supplier combinations. Performances of each supply portfolio are available in terms of relevant KPIs after the simulation. In this study we evaluate four KPIs, including purchasing costs, transportation costs, inventory costs and total backlogged demands. The fitness of a supply portfolio is determined as in (1), where α is the unit backlogging cost.

$$\begin{aligned}\text{Fitness} &= \text{Purchasing costs} + \text{Transportation costs} \\ &\quad + \text{Inventory costs} + \alpha \times \text{backlog} \qquad (1)\end{aligned}$$

Figure 4 shows the mean value of total costs of each generation. Note that the mean value converges very quickly within relatively small number of generations. One reason is that the solution space is relatively small. The best so far supply portfolio selects Supplier B from Far East as the unique supplier. The transportation mode is also the most economic one, namely boat plus truck. Considering that the purchasing costs is about 90% of the total costs, it is reasonable to find that the supplier which provides products in the lowest price is selected in this case.

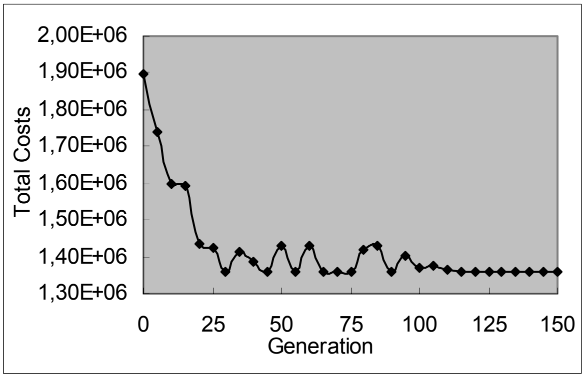

Figure 4: Mean Value of the Total Costs

7 CONCLUSION

The design of a global supplier selection approach has been a challenging optimization problem for many years. A significant number of methods and works were proposed (ex. AHP approach, mathematical programming, elimination and probabilistic methods) to solve the problem. Three main difficulties in developing effective selection methods are related to: 1) the qualitative and quantitative nature of the selection criteria, 2) the market behavior and 3) the short product life cycle (3 to 4 years or less). In order to select the best suppliers it is crucial to make a trade off between these tangible and intangible criteria some of which may be contradictory.

In this paper, a simulation-optimization approach using a genetic search method is proposed. This approach efficiently takes into account the randomness nature of the problem and proposes a solution to the problem. In this approach, the genetic search method, based on a fitness function, provides possible configurations of the selected suppliers, including transportation links, and an evaluation of each configuration based on some performance indicators (ex. purchasing costs, transportation costs, inventory costs and total backlogged demands) is realized using a performed simulator. A real life case study was presented and simulation results were given for the validation of the approach.

Concerning the future research work, we intend to add a partition in the string to represent the order assignment ratio. The parameter of the inventory policy can also be introduced in the string. Thus, the search space turns to infinite and the efficiency of the proposed simulation-optimization method can be further tested.

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REFERENCES

Barbarosoglu G., and T. Yazgac. 1997. An Application of Analytical Hierarchy Process to Supplier Selection Problem. *Production and Inventory Management Journal*, First quarter, 14-21.

Bensaou M. 1999. Portfolios of Buyer-Supplier Relationship. *Sloan Management Review*, Vol. 40, No. 4, 35-44.

Crow L. E., R. W. Olshavsky, and J. O. Summers. 1980. Industrial Buyer Choice Strategies : A Protocol Analysis. *Journal of Marketing Research*, Vol. 17, 34-44.

D'Amours S., A. Jabiri, and M. Levasseur. 2001. Les Processus de Catégorisation des Fournisseurs au sein des Entreprises de Classe Mondiale. *4ème Congrès International de Génie Industriel, France*.

Dickson G. W. 1966. An Analysis of Vendor Selection : Systems and Decisions. *Journal of Purchasing*, Vol. 1, No. 2, 5-17.

Dyer R. F., and E. H. Forman. 1992. Group Decision Support with the Analytic Hierarchy Process. *Decision Support System*, Vol. 8, 99-124.

Ellram L. M. 1990. The Supplier Selection Decision in Strategic Partnerships. *Journal of Purchasing and Materials Management*, Vol. 26, No. 4, 8-14.

Ghodsypour S. H., and C. O'Brien. 1998. A Decision Support for Supplier Selection Using an Integrated Analytic Hierarchy Process and Linear Programming. *International Journal of Production Economics*, No. 56-57, 199-212.

Golden B. L., E. A. Wasil, and P. T. Harker. 1989. *The Analytic Hierarchy Process : Applications and Studies.* New York, Springer Verlag.

Goldberg D. 1989. *Genetic Algorithms in Search, Optimization & Machine-Learning.* Addison-Wesley.

Holland J. H. 1975. *Adaptation in Natural and Artificial Systems.* University of Michigan Press, Ann Arbor, MI.

Kamath R., and J. Likert. 1994. A Second Look at Japanese Product Development. *Harvard Business Review*, November, 154-170.

Mobolurin A. 1995. Multi-Hierarchical Qualitative Group Decision Method : Consensus Building in Supplier Selection. *Proceeding of the International Conference on Applied Modeling, Simulation and Optimization*, USA, 149-152.

Soukup W. R. 1987. Supplier Selection Strategies. *Journal of Purchasing and Materials Management*, Vol. 26, No. 1, 7-12.

Thompson K. N. 1990. Vendor Profile Analysis. *Journal of Purchasing and Materials Management*, Vol. 26, No. 1, 11-18.

Weber C., J. R. Current, and W. C. Benton. 1991. Vendor Selection Criteria and Methods. *European Journal of Operational Research* 50, 2-18.

Weber C., and J. R. Current. 1993. A Multi-Objective Approach to Vendor Selection. *European Journal of Operational Research* 68, 173-184.

Wright P. 1975. Consumer Choice Strategies: Simplifying vs. Optimizing. *Journal of Marketing Research*, Vol. 12, 60-67.

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