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MULTIOBJECTIVE SUPPLIER SELECTION USING GENETIC ALGORITHM: A COMPARISON BETWEEN WEIGHTED SUM AND SPEA METHODS

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Abstract: *Supplier selection is one of the basic and most important activities of purchasing management. This activity often includes solving of multiobjective optimization problems with different and usually conflicting objectives. Modern supplier selection techniques involve novel multiobjective optimization algorithms based on computational application. In this paper supplier selection using genetic algorithm is presented. The authors used two different methods: weighted sum method and SPEA method. Weighted sum method belongs to category of Decision before Search methods. SPEA method is a member of Search before Decision group of methods. As criteria for selection optimization variance of quality and total costs are used. Results show that described methodology can be applicable for the practical purposes. Finally, comparative analysis of two different methods, used in this research, is presented*

Keywords: *Supplier selection, multiobjective optimization, genetic algorithms, strength Pareto evolutionary algorithm, weighted sum method.*

1. INTRODUCTION

Supplier evaluation and selection is the most sensitive activity because the identified suppliers have different weaknesses and strengths. Usually it requires precise assessment of suppliers' characteristics that are relevant for following selection.

Supplier selection process begins with suppliers' performance evaluation. After performance assessment is made, the next step is making selection decision. This process would be simple if only one criterion was used. However, there are, usually, a number of relevant criteria that must be satisfied for final vendor acceptance. In that case it is necessary to determine importance of each criterion for decision making process, i.e. to determine weight parameter that have to be assigned to each criterion before final vendors' evaluation [17].

Defining of criteria for supplier evaluation and selection is the major aspect of the purchasing function [4]. There are a number of studies addressed to this research field. One of the first studies was made by Dickson [3] who performed an extensive identification and analysis of criteria that were used in the selection of a firm as a supplier. His 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. Respondents had to assess the importance of each criterion on a five point scale from extreme to no importance value. Based on respondents' reply "quality" was selected as the most important criterion. Classification presented by Weber et al [15] based on analysis of all the articles published since 1966 showed that price, delivery, quality and production capacity and location were the most often treated criteria. On the other hand, study by Tullous and Munson [13] discovered that quality, price, technical service, delivery, reliability, and lead time were among the most important selection factors. This study was performed by analysis of eighty manufacturing firms.

More recently, Zhang et al [18] presented study based on 49 articles published between 1991 and 2003 which confirmed that net price quality and delivery were the most important supplier selection criteria. Finally, the review performed by Bross and Zhao [2] study concluded that the most valuable supplier selection criteria were cost, quality, service, relationship, and organization.

2. SUPPLIER SELECTION

Existing methods for solving supplier selection problems can be classified into three major categories.

First category contains methods based on elimination of suppliers which do not satisfy defined selection rule. For each chosen criterion must be defined minimal mark. Applying “conjunctive” rule [16], suppliers whose mark is lower than minimal mark are eliminated. Suppliers whose marks satisfy minimal marks of all chosen criteria go in next phase. Next phase is usually application of “lexicographic” rule [16] which implies selection of the most significant criterion for suppliers’ assessment. Supplier who satisfies chosen criterion much better than other supplier is selected.

Second category of supplier selection methods are probabilistic methods. One of the most famous methods is “Payoff Matrix” [10] which implies defining several scenarios of the suppliers’ future behavior. Then, for each scenario and each criterion we associate mark to supplier. Finally, for each supplier the total mark is computed. Supplier with stable total mark according to various scenarios is selected.

Third category refers optimization methods. In the optimization method we optimize an objective function by varying potential suppliers. Objective function can include only one criterion or a set of criteria. Also, each criterion can involve a set of constraints on its value. This kind of optimization methods are known as single objective optimization problems. The problem can be much complex if several different objective functions are involved. This kind of optimization problems are known as multi objective optimization problems.

If the objective function consists of only one criterion, supplier selection is very simple. Supplier with best performance with regard to chosen criterion will be selected. The much complex challenge is the selection of the most important criterion. A considerable number of companies in this case use total cost (direct costs, purchase costs, transport costs etc.) as criterion. So, after computing the total cost for each supplier purchase management selects the supplier which is the least expensive one [12]. On the other hand, a number of companies as the selection criterion use supplier quality. In any case, single criterion optimization is rarely in use today.

Multiobjective optimization is usually very complex and requires significant computational efforts. There are a number of different algorithms of fully multiobjective optimization such as VEGA (Vector Evaluated Genetic Algorithm**)** NSGA (Nondominated Sorting Genetic Algorithm), SPEA (Strength Pareto Evolutionary Algorithm) etc. This category of algorithms is based on evolutionary algorithms. Other approach implies transformation of multiobjective problem into single objective problem using weighted sum with predefined weights of each criterion (objective). In this paper we present supplier selection using multiobjective optimization based on weighted sum and genetic algorithm. In the next section we present general concepts of multi objective optimization. genetic algorithm. Key relations of our model for supplier selection and results of research are presented in the Section 4. Finally, in the concluding remarks we emphasize that the described method is generally applicable in this area of supply management.

3. GENETIC ALGORITHM

The term evolutionary algorithms (EA) or evolutionary strategies address a class of stochastic optimization methods which emulate the natural evolution. The origins of EAs can be found in the late 1950s, and since the 1970s several evolutionary methodologies have been proposed.

This class of optimization methods addresses genetic algorithms, evolutionary programming, and evolution strategies [1]. Very important characteristic of these methods is ability for relatively simple implementation of parallel processing. Because of their ability to solve high dimensional and highly complex optimization problems that are impossible to be solved with conventional, deterministic methods, this class of methods became important part of modern intelligent systems.

In this section we briefly present fundamentals of the one type of the evolutionary methods called genetic algorithms.

Genetic algorithm is a stochastic optimization technique invented by Holland [6] based on the Darwin principle that in the nature only “the fittest survive”. In order to realize this principle Holland introduced the basic phenomena of the biological evolution such as inheritance, crossover and mutation. So, in GA there is a set of individuals often called population. Each individual from population presents candidate solution of optimization problem.

The individuals are usually referred to as chromosomes. Each chromosome, i.e. candidate solution, represents decision vector made of decision variables and has fitness values that correspond to defined objective functions. In the vocabulary of genetic algorithms each decision variable in the chromosome is called gene.

Generally, genetic algorithm consists of following steps:

1. Initialization of population with random individuals,
2. Fitness evaluation of the individuals in the population,
3. Generation of new population, using crossover and mutation,
4. Selection of individuals according to their fitness using some strategy (e.g. a Roulette wheel selection),
5. Stop if terminating condition is satisfied (e.g., a fixed number of iterations), otherwise go to step 2

First step of genetic algorithm is initialization of population. In this step we generate individuals using random approach. So, each gene (decision variable) within the individual is generated randomly and independently. Due to specificity of optimization problem presented in this work we introduce here constraint that must be handled in algorithm execution. Sum of the genes (decision variables) within each individual must be equal to 1. Hence, generation of individuals have to be realized with the respect to this constraint.

In our research we have implemented crossover operator denoted basic crossover. This crossover operator involves two parents and produce two offspring (two new individuals) swapping their genes. Idea is to divide both parents' chromosomes in two segments at dividing point (gene), and then to swap obtained segments. Operator is stochastic one because the dividing point is chosen randomly each time operator is applied. In our case, additional normalization of offspring's is required. The schematic presentation of basic crossover operator is shown in Figure 1a [14].

The mutation of individuals (chromosomes) has the same effect as the mutation of living beings. So, in nature unpredictable changes of genes occur. These changes induce that characteristics of offspring differ from characteristics of parents. In genetic algorithm mutation operator simulate the mutation process found in the nature. In this work we realized the mutation operator as follows.

For randomly chosen individual from previous population we randomly chose two genes. Then, we increase the first gene with user defined value (e.g. 0.1) and second gene decrease with the same value. Again, in order to satisfy constraints of problem, normalization of chromosome must be applied. The schematic presentation of basic crossover operator is shown in Figure 1b [14].

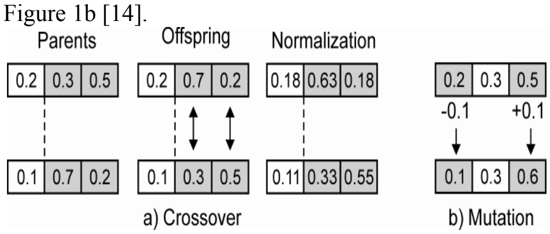

Figure 1. a) Basic crossover; b) Mutation [14].

During the execution of the one iteration of genetic algorithm there is a risk that the best solution (individual which best fits the objective functions) can be lost. In order to avoid that scenario we implemented elitism strategy. Elitism strategy assures that the best individual from previous population will be transmitted to the next generation without changes.

4. MULTIOBJECTIVE OPTIMIZATION

In single-objective optimization the optimal solution is clearly defined. This is because there is usually only one optimal solution. Unlike single-objective optimization in multiobjective optimization there is a set of alternative solutions (trade-offs).

These "optimal" solutions are usually called Pareto-optimal solutions. We can say that these solutions are optimal solutions because there is no other solution in the search space which is superior to them considering all objectives [19].

In the following text we present the basic definitions of multiobjective optimization theory based on Pareto dominance which are necessary for further discussion.

A general MOP (Multiobjective Optimization Problem) includes a set of n parameters (decision variables), a set of k objective functions, and a set of m constraints. Objective functions and constraints are functions of the decision variables. Generally we can say that the optimization goal is to:

maximize $\mathbf{y} = \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x}))$
subject to $\mathbf{c}(\mathbf{x}) = (c_1(\mathbf{x}), c_2(\mathbf{x}), \ldots, c_m(\mathbf{x})) \le 0$
where $\mathbf{x} = (x_1, x_2, \ldots, x_n) \in \mathbf{X}$ and $\mathbf{y} = (y_1, y_2, \ldots, y_k) \in \mathbf{Y}$

$\mathbf{X}$ denotes the decision space, $\mathbf{Y}$ denotes the objective space, $\mathbf{x}$ is the decision vector, and $\mathbf{y}$ is the objective vector. The constraints are defined as $\mathbf{c}(\mathbf{x}) \le 0$ and determine the set of feasible solutions.

The second definition regards to the term of Pareto dominance and can be presented as follows. Here we consider that optimization problem implies maximization of objective functions

For any two decision vectors a and b, we can differ three cases:

1. $\mathbf{a} \succ \mathbf{b}$ (**a** dominates **b**) if $\mathbf{f}(\mathbf{a}) > \mathbf{f}(\mathbf{b})$
2. $\mathbf{a} \succeq \mathbf{b}$ (**a** weakly dominates **b**) if $\mathbf{f}(\mathbf{a}) \ge \mathbf{f}(\mathbf{b})$
3. $\mathbf{a} \approx \mathbf{b}$ (a is indifferent to b) if $\mathbf{f}(\mathbf{a}) \ngeq \mathbf{f}(\mathbf{b})$ and $\mathbf{f}(\mathbf{b}) \ngeq \mathbf{f}(\mathbf{a})$

If the optimization problem implies minimization of objective functions the relations are the same but with adequate symbols ($\prec, \preceq, \approx$), respectively.

In solving an MOP, we can identify two distinct phases.

The first is search for optimal solutions regarding to considering objectives, and the second is decision making, i.e. choosing the appropriate one among the number of solutions within the set of Pareto optimal solutions, obtained during the search [7].

Comparing to single-objective optimization, search space is very often even larger and more complex what induces inability of use of some exact optimization methods such is linear programming [11].

The second phase is related to the problem of selecting a suitable compromise solution from the Pareto-optimal set. With regard to the fact that Pareto optimal set consists of solutions that are non dominated to each other it is obviously that a human decision maker (DM) have to make trade-offs between conflicting objectives.

5. STRENGTH PARETO EVOLUTIONARY ALGORITHM (SPEA)

In this section we present the fundamentals of Strength Pareto Evolutionary Algorithm (SPEA). The following text refers [19]

The first step in strength Pareto evolutionary algorithm is initialization of the population. Within this step empty external set $\overline{\mathbf{P}}$ is generated.

After initialization the main loop executes until termination criteria is satisfied. The main loop of the algorithm is presented in Figure 2. At the beginning of each loop iteration, the external set $\overline{\mathbf{P}}_i$ is updated.

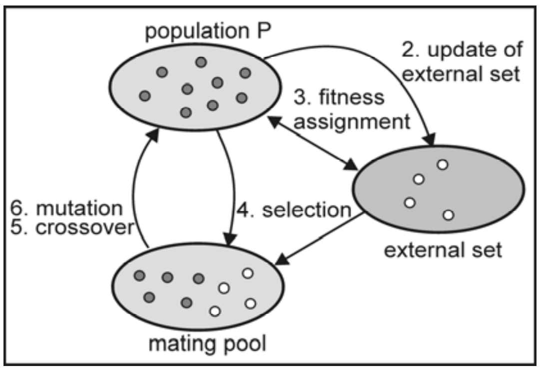

Figure 2. Schematic presentation of SPEA procedure [19]

Updating implies copying of the nondominated solutions from population $\mathbf{P}_i$ and removing solutions that are weakly dominated. At the end of this step, in order to avoid clustering, reducing of the number of individuals is performed. Then, individuals in $\overline{\mathbf{P}}_i$ and $\mathbf{P}_i$ are evaluated and assigned fitness values. In the next step mating pool is generated by union of population $\mathbf{P}_i$ and external set $\overline{\mathbf{P}}_i$.

The next step is selection operation performed on previously generated mating pool. In this work roulette wheel selection is used.

Finally, crossover and mutation operators are applied as usual. If the termination criteria is not satisfy algorithm begins new iteration.

5. SUPPLIER SELECTION USING GA

As we found in literature listed in the Section 2, the most frequently used criteria for supplier selection are the maximization of quality and minimization of total costs. In our research we analyzed variance of suppliers' total quality and total cost for the chosen number of deliveries of single raw material, realized in the previous period. We observed 40 deliveries of six suppliers. For each delivery quality rating is performed. Also, during observed deliveries total costs per unit of raw material and per supplier are assumed to be constant.

So, we can say that total amount of raw material delivered in single delivery of all suppliers can be calculated as:

$$A_{total} = \sum_{i=1}^{n} a_i \qquad 1)$$

where a_i denotes amount of raw material delivered by *i-th* supplier and A_{total} denotes total amount delivered by all suppliers.

Using Eq. 1 we can introduce weight parameter w_i which denotes participation of *i-th* supplier's amount in total amount of delivered raw material.

$$w_i = \frac{a_i}{A_{total}} \qquad 2)$$

By introducing weight parameter we can define the total cost per unit of raw material as follows:

$$C_{total} = \sum_{i=1}^{n} w_i C_i \qquad 3)$$

where C_i denotes cost per unit of raw material and C_{total} denotes total cost per unit of raw material.

Also, by introducing weight parameter we can define quality of each delivery made by all suppliers.

$$Q_k = \sum_{i=1}^{n} w_i Q_{k,i} \qquad 4)$$

where Q_k denotes quality of *k-th* delivery and $Q_{k,i}$ denotes quality rating of *i-th* supplier his *k-th* delivery.

It is obviously that variance of quality depends on variance of quality of each delivery of each supplier. Variance of total quality can be defined using standard deviation in the following manner.

$$Var = \sqrt{\frac{\sum_{k=1}^{m} \left(Q_k - \overline{Q}\right)^2}{m}}, \ for\ k = 1, \ldots, \qquad 5)$$

where m denotes number of deliveries and $\overline{Q}$ denotes average of quality considering all deliveries. The main goal of this work was to determine weights (participation of each supplier) which would lead to minimization of quality variance and minimization of total costs.

In order to demonstrate application of described methods for supplier selection problems we used historical data. Historical data consist of quality ratings for 40 deliveries performed by 6 suppliers. Quality ratings are in the range from 0 to 100 and total costs per unit of raw material are expressed in euros.In the table below standard deviation and mean value of total quality rating, and total costs of each supplier are presented.

Table 1. Quality mean value and standard deviation and total costs per unit of raw material

	Sup. 1	Sup. 2	Sup. 3	Sup. 4	Sup. 5	Sup. 6
Quality. Mean Val.	78.9	82.2	86.7	84.3	80.0	87.0
Quality St. Dev.	9.5	10.0	9.3	7.2	5.8	3.5
Costs (€)	0.0113	0.0105	0.0125	0.0131	0.0152	0.0180

5.1. Weighted Sum Method

In order to apply weighted sum optimization method for solving of described optimization problem we had to define adequate mathematical model. Formal definition optimization problem would be as follows:

$$\text{Minimize } \lambda\sum_{i=1}^{n} w_i C_i + (1-\lambda)\sqrt{\frac{\sum_{k=1}^{m}\left(Q_k-\bar{Q}\right)^2}{m}} \qquad 6)$$

Subject to:

$$\sum_{i=1}^{n} w_i = 1, \quad 0 \le w_i \le 1 \quad and \quad 0 \le \lambda \le 1 \qquad 7)$$

where m denotes number of deliveries and n denotes number of suppliers.

Eq. (6) the case λ = 0 represents minimum of quality variance and λ = 1 represents minimum expected costs. Values of λ satisfying 0 < λ < 1 represent an explicit trade-off between quality variance and costs, generating solutions between the two extremes λ = 0 and λ = 1. Eq. (7) ensures that the proportions add to one.

5.2. SPEA Method

As we said before, SPEA method is full multiobjective optimization method. In this case, we don't need to merge all objectives in one single objective function. Instead, we have to define each objective function separately. So, formal definition of described optimization problem would be as follows:

$$\text{Minimize } C_{total} = \sum_{i=1}^{n} w_i C_i$$

$$\text{Minimize } Var = \sqrt{\frac{\sum_{k=1}^{m}\left(Q_k-\bar{Q}\right)^2}{m}}$$

$$\text{Subject to } \sum_{i=1}^{n} w_i = 1, \quad 0 \le w_i \le 1$$

where m denotes number of deliveries and n denotes number of suppliers.

6. RESULTS

The results of optimization, using two different approaches are presented in the Figure 3. Pareto optimal solutions, obtained using weighted sum method, are denoted with no filled square points. As it can be seen, we examined 6 different λ values, so 6 optimized solutions are presented.

Pareto optimal solutions, obtained using SPEA method, are denoted with filled square points. Using this optimization method we obtained 11 different solutions.

Also, in order to demonstrate improvement made by performed optimization no optimized solutions are included (filled circle points).

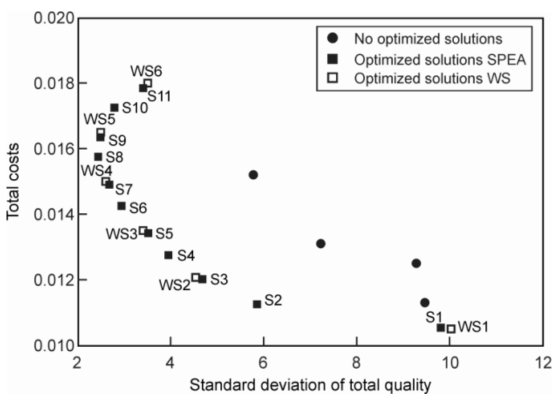

Figure 3. Optimized solutions for supplier selection problem

Each solution in optimal set implies different delivery portions of observed suppliers.We can see that optimized solutions (squared dots) give significantly better trade-off between variance of quality and total costs.

Also, as it can be seen, there is no significant difference between Pareto optimal solutions obtained using weighted sum method and using SPEA method.

In the Table 2 are presented weight parameters obtained by optimization using weighted sum method. Each set of weights corresponds to each point in the Figure 3

Table 2. Weight parameters obtained by optimization (Weighted sum method)

Points/ weights	*w1*	*w2*	*w3*	*w4*	*w5*	*w6*
Point WS1	0.00	1.00	0.00	0.00	0.00	0.00
Point WS2	0.24	0.28	0.20	0.21	0.08	0.00
Point WS3	0.14	0.19	0.15	0.18	0.17	0.17
Point WS4	0.09	0.09	0.10	0.13	0.17	0.42
Point WS5	0.03	0.01	0.05	0.08	0.16	0.67
Point WS6	0.00	0.00	0.00	0.00	0.00	1.00

In the Table 3 are presented weight parameters obtained by optimization using SPEA method. Each set of weights corresponds to each filled square point in the Figure 3.

Table 3. Weight parameters obtained by optimization (SPEA method)

Points/weights	*w1*	*w2*	*w3*	*w4*	*w5*	*w6*
Point S1	0.02	0.97	0.01	0.00	0.00	0.00
Point S2	0.31	0.44	0.22	0.02	0.00	0.00
Point S3	0.22	0.29	0.21	0.21	0.08	0.00
Point S4	0.17	0.22	0.19	0.19	0.18	0.05
Point S5	0.14	0.18	0.16	0.17	0.18	0.17
Point S6	0.11	0.14	0.13	0.15	0.18	0.29
Point S7	0.09	0.09	0.11	0.13	0.18	0.40
Point S8	0.06	0.05	0.08	0.11	0.18	0.52
Point S9	0.03	0.01	0.05	0.09	0.18	0.64
Point S10	0.00	0.00	0.01	0.05	0.16	0.78
Point S11	0.00	0.00	0.00	0.01	0.03	0.96

5. CONCLUSIONS

In this paper we presented solving of multiobjective supplier selection problem using two different approaches. As criteria for selection optimization we used variance of quality and total costs.

The first approach is based on aggregation of objectives (criteria) into single objective using predefined ponders for each objective. Ponders (weights) have to be defined by decision maker. This multiobjective optimization approach is known as *decision making before search* [8], [7]. This approach implicitly includes preference information given by the decision maker and has the advantage that the classical single-objective optimization strategies can be applied without modifications.

The first drawback of this approach is that weights (importance) of each objective have to be defined before optimization.

The second drawback lies in the fact that one optimization process gives only one optimal solution. Every change of objective weights induces new optimization process. In this paper we presented optimal solutions obtained using six different values of weight parameter. For each weight parameter value we performed one optimization calculation.

The second approach implies application of fully multiobjective optimization algorithms such is SPEA method, used in this paper. In this case optimization is performed considering each objective separately and the result of the search process is a set of Pareto-optimal solutions. So, decision maker can choose the most suitable solution. In the literature this approach is known as *search before decision making* [8], [7]. Advantage of this approach is that one single optimization calculation gives the set of optimal solutions. On the other hand, drawback of this approach lies in the fact that decision maker can’t influence on importance of any objective.

The application of presented approaches depends on affinity and existence of domain knowledge of decision maker.

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