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A Fuzzy Logic and Genetic Algorithm based Supplier Performance Evaluation Methodology for an Effective Supply Chain

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Abstract

In this paper, an attempt has been made to evaluate the supplier performance by adopting evolutionary fuzzy system owing to the linguistic nature of the attributes associated with the suppliers and manufacturing units. The proposed methodology provides reasonably good performance when applied to a process industry for evaluation of supplier's performance.

1. Introduction

Managing of Supply Chains has gained importance for competing in the business environment in this decade. The objective of the supply chain management is to have the right product at right place at the right time. A supply chain is a network of facilities that procure raw materials, transforms them to intermediate goods and then to finished products, and delivers the products to customers through a distribution system. There are three stages in the supply chain: procurement, production and distribution.

In order to ensure the uninterrupted supply of items, purchasing manager need to periodically evaluate supplier's performance in order to retain those suppliers, which meet their requirement in terms of several performance criteria. The evaluation element typically consists of identifying the attributes, factors relevant to the decision and then measuring each vendor by considering each of the relevant factors.

It is worth to mention here that in some of the recent studies, the essential requirements advocated for suppliers' selections are quality, cost, delivery, flexibility and response [1]. In recent years, several proposals for evaluating the performance of the suppliers have been reported in the literatures. Notable among them: Categorical method, weighted point method, and cost ratio method [2, 3]. Soukep [4] suggests supplier selection strategies using weighted point method. Narasimhan [5] and Tam [6] propose an Analytic Hierarchic Process (AHP) based methodology to supplier selection. Li et al. [7] propose a new supplier performance measure employing the concept of dimensional analysis. They suggest a standardized unitless rating (SUR) by combining the weighted average of qualitative and quantitative scores associated with each supplier. Petroni and Braglia [8] use Principal Component Analysis for Vendor selection. Narasimhan et al [9] propose Data Envelopment Analysis (DEA) for supplier evaluation and rationalization. The above mentioned methodologies have some advantages under specific condition only. But none offers a generic methodology, which can combine several criteria or attributes into a single measure of supplier performance. Owing to their diverse and linguistic nature, supplier attributes usually need to be categorized prior to further analysis. A cross-functional team is required to rate the supplier' attributes in linguistic descriptions like very low, low, medium, high, very high etc. Linguistic assessment of suppliers is to be carried out based on several criteria, such as quality, response to special orders, delivery performance and price. Because of the imprecise nature of linguistic attributes associated with suppliers, inconsistencies in the judgment are bound to crop up regarding the grading of supplier performance. To deal with these inconsistencies, fuzzy method is suggested to convert the suppliers' linguistic attributes into fuzzy numbers and relative supplier performance is assessed using fuzzy arithmetic.

In this paper, an evolutionary fuzzy system-based methodology is suggested for a more precise and effective assessment and evaluation of suppliers. It maintains a population of fuzzy rule sets with their membership functions, and uses the genetic algorithm to evolve a feasible fuzzy rule base. One of the key considerations in designing the proposed evolutionary fuzzy system is the generation of fuzzy rules as well as the membership functions for each fuzzy set. While dealing with a few input variables, the cross-functional teams are used to generate the fuzzy rules for several performance attributes. Since the number of fuzzy rules increase exponentially with increase in number of input variables, it is difficult for the cross functional team to define a complete fuzzy rule base for a good decision support system. It is essential to develop a genetic algorithm (GA) based methodology to evolve the optimal set of fuzzy rule base. Currently several researchers [10, 11] recommend evolutionary fuzzy systems in the areas of data classification, prediction and control problems.

2. Fuzzy System

In many real world applications, fuzzy systems that make use of linguistic rules are aptly suited to describe the behavior of computer systems problem, which is difficult to model mathematically. Fuzzy theorists used fuzzy sets to

represent the non statistical, uncertainty and approximate reasoning, to real life data. The membership value $m_A(x)$ represents the grade of membership of x in A. The larger $m_A(x)$, stronger the grade of membership for x in A. In a n-input-single-output fuzzy system, the fuzzy rules have the following general format:
Rj : IF X_1 is $Y_{1,j}$ And X_2 is $Y_{2,j}$ And …………… And X_n is $Y_{n,j}$ Then Y is Z_j
Where the variables X_i (i = 1, ………, n) appearing in the antecedent parts of the fuzzy rules R_j are called the input linguistic variables, the variable Y in the consequent part of the fuzzy rule R_j is called the output linguistic variables, the fuzzy sets $Y_{i,j}$ are called the input fuzzy sets of the input linguistic variable X_i of the fuzzy rule R_j , and the fuzzy set Z_j is called the output fuzzy set of the output linguistic variable Y of the fuzzy rule R_j .

A fuzzy expert system is defined if and only if the rule sets and membership functions associated with its fuzzy sets are defined. All the fuzzy rules in a fuzzy system are fired in parallel mode. The working of a fuzzy expert system can the described as follows :

i) Evaluate the values of fuzzy membership by energizing the inputs
ii) Obtain the fuzzy rules which are fired in the rule set .
iii) Adopting AND operator, club the values of membership for each energized rule
iv) Search rule activation membership values supported by the min-max compositional rule to obtain the appropriate output fuzzy membership value.
v) Determine the value of each output variable by defuzzification which is carried out by the weighted average method.
vi) Take decisions according to the output values.

In this paper weighted average method is adopted to defuzzify the fuzzy output data as this methodology is only valid for symmetric output membership function. based on the crisp output data, practical decisions can be made to solve the problems. In this paper based on the crisp output data, the suppliers performance are graded.

3. Evolutionary Fuzzy Systems

It has been observed that majority of the existing applications, the fuzzy rules are generated by experts and decision makers conversant with the problem, with only a few inputs. The possible number of fuzzy rules for a given system grows exponentially when the number of input variable increases. For example in the evaluation of a supplier performance with 10 attributes and each attribute consists of 5 linguistic descriptions (very low, low, medium, high, very high) then the possible number of fuzzy rules are 5^{10}. It is too difficult if not impossible for an expert to define a complete rule set for assessing the system performance. There are several methods like clustering algorithms, pattern classification methods etc. to practice an automated way to design fuzzy system. These methods are possessing a drawback related to the extractions of rules where it is possible that these rules become the independent of membership functions leading to degraded performance of the fuzzy system obtained especially in the case of complex system problem with large number of input variables. In several cases, the systems performance are found to be improved by tuning the membership functions and selecting suitable fuzzification and defuzzification methods. In this paper, *evolutionary fuzzy system* have been employed in which the fuzzy rule set, number of rules inside the rule set are generated using a powerful and intelligent search algorithm known as Genetic Algorithm to assess the supplier performance. Genetic Algorithms have recently found its growing applications in solving the several types of linear and non-linear optimization problem. GA is a matured tool and interested readers are advised to refer Goldberg[12]. This fact motivated the researchers to use this intelligent optimization tool for the generation of a set of fuzzy rules required to design the fuzzy rule base. The various constituents of the proposed evolutionary fuzzy system are described as follows.

3.1 Representation

The first important consideration while designing a fuzzy expert system using GA is the representation strategy adopted to encode the fuzzy system into the chromosome. A fuzzy system is well defined only when the fuzzy rule base and the membership functions associated with each fuzzy set of a variable are specified. Thus, it is practically realized that to completely represent a fuzzy expert system, each chromosome must encode all the requisite information about the rule sets and the membership functions. The fuzzy rules in the rule base and the number of such fuzzy rules that are associated with the problem are to be evolved using GA. In order to reduce the search space, it is advocated that the maximum number of rules concerning any problem is fixed in advance. After performing exhaustive trial and error experimentation, the maximum number of acceptable rules undertaken in this study is limited to 40. Then the total length of the chromosome representing the system is 1+5*(40) =201, and the system can be represented as $S_1S_2S_3S_4S_5S_6$……………$S_{57}S_{58}S_{59}$……………$S_{140}S_{141}$… ……………. $S_{199}S_{200}S_{201}$,
Where S_1 represents the number of rules varying between 1 and 40, S_2,S_3,…..S_6 encodes the first fuzzy rule in the rule set and S_{197},S_{198} …….S_{201} represents the last fuzzy rule in the rule set. S_1 denotes the number of possible rules that are used to design the rule base. However, it is observed that each rule may not be feasible. A rule with a zero antecedent or consequent part is an infeasible rule and should be excluded from the fuzzy rule base. In order to ensure that the chromosome contains no infeasible rules, the fitness value corresponding to the chromosome is assigned to a very small floating number [0,1], so that these chromosomes do not pass over to the next generation.

3.2 Fitness Function

While the genotype representation encodes the rule base into a integer string, the fitness function evaluates the performance of the rule base. For prediction and estimation problems, the mean-square error or absolute difference error related function is most commonly used. In this paper, the mean square error function is determined to evaluate the fitness of the chromosomes.

$E = 1/N\ \Sigma(o_i-e_i)^2$ ... (1)

Where N is the number of evolved fuzzy rules.,

o_i and e_i are the i^{th} expected outputs obtained by assigning priorities to the input variable

Fitness Value = 1/ (1+E) ... (2)

Chromosomes with higher fitness value are carried to the next generation.

3.3 Crossover Operator

Crossover is a process by which two parent strings recombine to produce two new offspring strings. An overall probability is assigned to the crossover process. Given two parent chromosomes, the algorithm invokes crossover only if a randomly generated number in the range of 0 to 1 is greater than crossover rate (it is also known as crossover probability), otherwise the strings remain unaltered. This probability is often in the range of 0.65-0.80.

3.4 Mutation Operator

After crossover, normally strings are subjected to mutation. Mutation operator randomly alters few composition of a string to produce a new offspring instead of recombining two strings. In a traditional genetic algorithm, mutation of a bit involves flipping it : changing a "0" to "1" or vice versa. It is found that the chromosome representing the fuzzy expert system is integer based instead of binary based i.e., each element of the string has an integer range representing the various states of the variable (input / output). The mutation operator used is thus a bit different than that used in binary encoding. Each time an element is chosen to be mutated, it is increased or decreased by replacing it by an integer in the range[1, 5] excluding the present value of the element . The integers of the string are independently mutated i.e., the mutation of the element does not influence the probability of mutation of another element.

4. Computational Exercise

The supplier performance is graded based on the attributes, which were selected from both the supplier and product's view point. They are namely quality rating, delivery performance, price rating, and service rating. In order to evolve the fuzzy rule base using Genetic Algorithms, a good fitness function is essential. Here, a least mean square function is adopted for fitness measurement, where the expected outputs are determined by prioritizing the attributes. Each feasible fuzzy rule that is evolved in the rule base has the maximum prioritized attribute in the first position, the next prioritized attribute in the second position and like wise. These priorities are analogous to weightages that are assigned to the attributes and reveals the relative importance among themselves. The fuzzy membership functions associated with the fuzzy sets of each inputs are left-triangle, triangle, triangle, triangle, and right-triangle corresponding to the linguistic descriptions very low, low, medium, high and very high. The ranges and the overlap area of the membership functions are fixed. A triangular fuzzy membership function has been adopted for the representing the fuzzy sets of the output variable.

5. Conclusions

Supplier performance evaluation is one of the important ingredients for the successful implementation of the strategies of supply chain. Several recent studies with regard to suppliers performance were critically examined. A novel methodology based on the fuzzy logic and genetic algorithm is employed to assess the performance of supplier.

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