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Managing Uncertainty in Supply Chain Operating Cost Using Genetic Algorithm

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1. Introduction

Supply chain uncertainty has been captured in various forms like supply uncertainty, production uncertainty and demand uncertainty. Uncertainty refers measuring the degree of differences between the models and the respective real systems values or between the estimation of variables and their true values [1]. The uncertainty can be caused by the errors associated with the model itself and the uncertainties of the model inputs.

The significant part of managing uncertainty is identifying as many sources and factors of uncertainty as possible [10]. For production planning, one typically needs to determine the variable production costs, including manufacturing costs, Labour cost, materials cost, inventory holding costs, and any relevant resource acquisition costs[9].

The identification the various sources and factors of uncertainty in manufacturing/production environment has been done here [4]. The main purpose of this paper is to minimize production costs. The fundamental concern of manufacturing resources planning is to guarantee that the best promising quantity of the item is released at the lowest costs within some given constraints of the system like availability of the resource(s) in need[5]. A Genetic algorithm is proposed that uses a set of crossover and mutation operators for solving the problem.

A global supply chain is a very large-scale system of organizations, people, technology, activities, information, and resources involved in moving a product or service from supplier to end customer [8]. Supply chain complexity will vary with the size of the business and the intricacy and numbers of items that are manufactured [3].

To ensure that the supply chain is operating as efficient as possible and generating the highest level of customer satisfaction at the lowest cost, companies have adopted supply chain management (SCM) processes and associated technology [2].

Supply chains tend to increase in complexity and the involvement of numerous suppliers, service providers, and end consumers in a network of relationships causes risks and vulnerability for everyone [7].

Uncertainty relates to the situation in which there is a total absence of information or awareness of a potential event occurrence, irrespective of whether the outcome is positive or negative [6]. The terms risk and uncertainty are frequently used interchangeably As firms move to leaner operating models and increasingly leverage global sourcing models, uncertainty in both supply and demand is growing along with supply chain complexity [11].

To improve the overall performance of supply chain, the members of supply chain may behave as a part of a unified system and coordinate with each other. Thus “coordination” comes into focus.

1.1 Factors of uncertainty

Uncertainty can be measured by the frequency of its occurrence, and analyzing the relative contribution and resulting effect on delivery performance can quantify whether the impact is minor or major. Koh and Saad (2003) identified eight uncertainties that are most likely to affect customer delivery performance. These are external late supply, internal late supply, planned set-up time exceeded, machine break-downs, labor unavailability, tooling unavailability, demand batch size enlargement and customer design changes[2],[3].

Their simulation output highlighted four uncertainties that have significant effects to PDL (parts delivered late) and FPDL (finished product delivered late). These are external late supply, machine breakdowns, demand batch size enlargement and customer design changes. The concept of ‘yield factor’ is used to embrace system uncertainties.

A composed yield factor relates the quantities of required inputs to satisfy a demand of specified output when the system uncertainties cause losses of articles in different levels of the production process. Therefore, the composed yield factor is a function of the prominent production factors in the different stages of the process.

1.2 Effects of and measures for uncertainty

Uncertainty can be measured by the frequency of its occurrence, and analyzing the relative contribution and resulting effect on delivery performance. It can quantify whether the impact is minor or major. Many conceptual and mathematical models are proposed and used to manage competitive production/manufacturing Uncertainties in manufacturing have heterogeneous effects due to the interrelationships between resources and operations[6].

The lead-time and demand uncertainties are individually and interactively significant determinants of system performance (Brennan, L. and S.M. Gupta, 1993). Lawrence and Sewell (1997) found that as processing time uncertainty increases, simple dispatch heuristics provide performance comparable or superior to that of algorithmically more sophisticated scheduling policies. Again increasing manufacturing flexibility leads to increased performance and to knob the uncertainty (Swamidass, P.M. and W.T. Newell, 1987).

2. Methods

In building a GA methodology to solve the supply chain sourcing problem, six fundamental issues that affect the performance of the GA must be addressed: chromosome representation, initialization of the population, selection strategy, genetic operators, termination criteria, and evaluation measures. In the following subsections, these issues are introduced and described specifically for the proposed multi-objective GA.

2.1 Chromosome Representation

For any GA, a chromosome representation is needed to describe each individual in the population. Chromosome representation determines how the problem is structured in the GA, as well as the genetic operators that can be used. For the sourcing decision, the chromosome representation in this case is fairly straightforward. Notice, that not all combinations of the decision variables constitute a feasible solution.

2.2 Initialization of the Population

The initial population is formed randomly based on the upper and lower bound for each of the decision variables in a chromosome using a uniform distribution.

2.3 Selection Strategy

Selection of parents to produce successive generations is very important in driving the search. The goal is to give more chance to the "fittest" individuals to be selected. For each selection scheme, probabilities are assigned to the individuals. The better individuals have higher probabilities.

Normalized Individuals are first ranked from best to worst according to their fitness values. Then each individual is assigned a probability based on the rank from a truncated geometric distribution (Joines et al. 1996). In the original NSGA-II method, u a tournament selection is used where the tournament is based on the *n* operator. Since the population is sorted from best to worst, the normalized geometric ranking scheme does not require any more sampling or sorting as does the tournament selection.

2.4 Genetic Operators

Reproduction is carried out by application of genetic operators on selected parents. Four mutation (Boundary, Uniform, No uniform, and Multi-No Uniform) and three crossover operators (Simple, Arithmetic, and Heuristic) are used based on the representation. Continuous variables use the version by Michalewicz (1996) while the discrete variables use the modifications by Joines et al. (1996).

2.5 Termination Criteria

The GA is terminated after a specified number of generations.

2.6 Evaluation Measure

Genetic algorithms rely on the simple premise of using natural selection as a means of solution elimination. The objective function is the driving the force of the GA search. In this research, instead of performing an analytical function evaluation, each solution is simulated to determine its performance. Because the simulation is based on a particular forecasted demand level and the answers generated need to be as robust as possible.

3. Fitness Function

Fitness functions ensure that the evolution is toward optimization by calculating the fitness value for each individual in the population. The fitness value evaluates the performance of each individual in the population.

The fitness function is given by:

$$\boxed{F(x) = -(x(1) + x(2) + x(3))}$$

Where:
x(1):Materials cost
x(2):Manufacturing cost &Plant cost
x(3):Labour cost

Variables:
Mc –Manufacturing cost
Pc-Production cost per unit
Lw-Labour wages
Cm-Cost of raw materials
Cp-Cost of running plant
Oc-Operating cost
Manufacturing cost: Mc=Pc+Cp

Operating Cost Oc=Mc+Lw+Cm

4. Experiment

The Proposed work considers the uncertainty of cost in production scenario. It develops a algorithm for managing uncertainty by minimizing manufacturing cost by crossover & mutation operators.

Uncertain Data Managing Genetic Algorithm : (UDMGA)

Step1. (Initialization) Choose population size *N* based randomly based on the upper and lower bound for each of the decision variables in a chromosome .Let the generation number t = 0.

Step2. (Crossover) Choose the parents for crossover from *P* (*t*) with probability *c p*. If the number of parents chosen is based on multi objectives, then in *P* (*t*), randomly match every two parents as a pair and use the proposed crossover operator c1 to each pair to generate two offspring. All these offspring constitute a set denoted by *O*.

Step3. (Local Search) For each offspring generated by crossover, the proposed local search scheme is used to it to generate an improved offspring. All these improved offspring constitute a set denote by 1 *s*.

Step4. (Mutation) Select the parents for mutation from set 1 *s* with probability *m p*. For each chosen parent, four mutations (Boundary, Uniform, No uniform, and Multi- No

Uniform) are used to it to generate a new offspring. These new offspring constitute a set denoted by 2*s*.

Step5. (Selection) Select the best *N* individuals among all the generated set G as the next generation population *P* (*t* +1), let *t* = *t* +1.

Step6. (Termination) If termination conditions hold, then stop, and keep the best solution obtained as the approximate global optimal solution of the problem; otherwise, go to step 2.

5. Discussion and Results

UDMGA Algorithm is applied to an inventory control system in a supply chain. The Uncertainty regarding the production cost will affect the profit margins of any business entity. In a production system, there are various factors that play a significant role. The input data is collected from Normalized data of UK based ASTEL computers production dataset (Table 1).

The two initial chromosomes “375 20 38’ and “385 53 57” are generated at the beginning of the genetic algorithm. These initial Chromosomes are subjected for the genetic operators, Crossover and Mutation. The resultant chromosome thus obtained again processed with repeat crossover and mutation that it moves towards the best chromosome after the each iterative execution. Hence at the end of the execution of 100 iterations, best chromosome '382.4, 31.0, 48' is obtained as shown in figure 1.

While applying the genetic algorithm with the past records, it can be decided that controlling this resultant chromosome is sufficient to reduce the total operating cost by due to the fluctuating roduction or labour or machine cost.

Table 1: Manufacturing Cost Dataset B

Prodn Id	Manuf. Cost(Pc) $	Labour wages(Lw) $	Cost of Materials(Cm) $
001	385	20	38
002	385	20	38
003	460	53	57
004	460	57	60
005	375	53	57
006	390	25	53
007	390	44	60
008	399	46	71
008	399	49	67

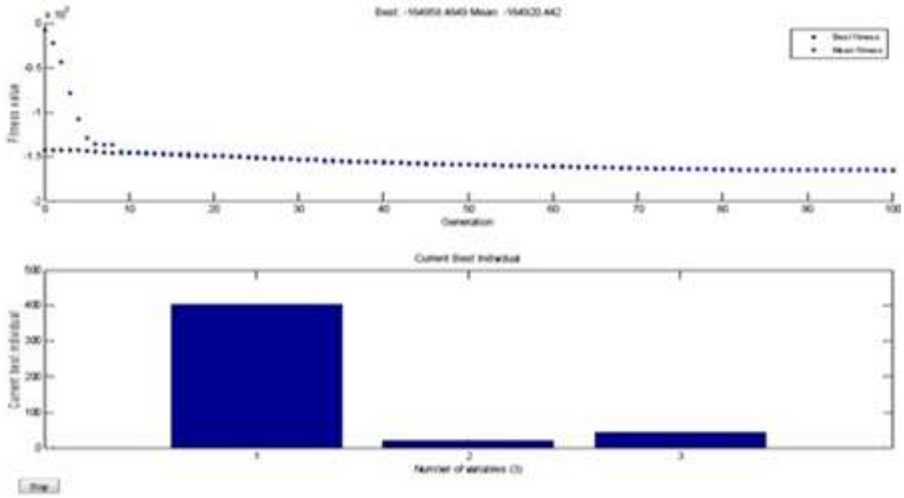

Figure 1: Result obtained by GA tool implementation

6. Conclusion

The Genetic Algorithm optimizes the total operating cost by optimizing the production variables like manufacturing, labor and machine cost. Thus removing uncertainty in production cost evaluation .This can lead to better forecasting of production cost and thereby achieve higher performance levels. MATLAB is used to obtain best solution.

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