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A stochastic simulation based genetic algorithm for a production repair model

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Abstract

This paper deals with a stochastic production repair model with chance constraints. A solution to such problems has great importance to the managers because such a solution serves as an invaluable tool for them in the process of developing a production plan to their companies. The common way of tackling such a problem is to derive the crisp equivalent of the original problem. This is possible if the parameters involved in the chance constraint follow some specific distribution or if we can estimate or approximate the chance constraints using some estimation procedure or numerical technique. In this paper, we first formulate a multi-product, single period and single plant chance constraint programming model having production and repair work simultaneously. The uncertainty about the cost, resources and man hour required to repair a product, arrival of products for repair, resources and manhour availabilities bring randomness to the formulated model. To solve the mathematical model, we propose a stochastic simulation based genetic algorithm. This algorithm can deal the stochastic parameters having any possible distribution. Finally, a numerical example is presented to prove the efficiency of the proposed algorithm.

Keywords: Chance Constraint, Stochastic Simulation, Production Planning, Genetic Algorithm.

1. Introduction

Production planning is one of the most important process for every company. It provides a great deal of decisions to adjust the industrial resources of a company in order to meet demand over the time periods. In other words, the purpose of production planning is to establish production rates in order to achieve management goals.

In the literature, there are large number of models on production planning (Karimi et al. (2003), Glock et al. (2014), Adulyasak et al. (2015)). The linear cost model includes fixed and variable work forces. The lot-size models includes uncapacitated and capacitated lot-size models. Also, there are quadratic cost models, goal programming models, general cost models. The production planning problem with machine failure is although considered by Gajpal and Nourelfath (2014) and Gajpal and Nourelfath (2015). But the issue of repair work within a valid warranty period of new products is not considered in these models.

The aim of this paper is to formulate a general mathematical model for describing a production plan for a company which produces several products and at the same time it accepts its out of order products having a valid warranty period for repair. The repair of products within a valid warranty period has been considered here because the warranty on products, now a days, is a common and important phenomenon for almost every company. The main interest is to find an optimal production policy that satisfies the objectives of the study (i) maximize the number of products and (ii) minimize total production, holding, regular and overtime labor costs for the whole production run subject to some chance constraints.

The chance constraint programming (CCP) is a common way of modelling uncertainty in mathematical programming problems if a decision has to be taken prior to full information about the random parameters of the problem. The approach followed in the CCP consists in fixing certain level of reliability for random constraints. CCP has been introduced into the Stochastic Programming literature mainly through the exposition of Charnes and Cooper (1959) and since then has been developed and applied by Kataoka (1963), Panne and Popp (1963), Jiang and Guan (2016) and others.

Growe (1997) presented a non-parametric estimation procedure for chance constraint stochastic programs where the random parameters appear on the right-hand side of linear constraints for the decision variable. Considering the random parameters as normal with known mean and variance Feiring and Sastri (1990) obtained the equivalent deterministic model of the original production planning problem. But this paper made many assumptions about the stochastic parameters. It is quite convenient and acceptable if we do not impose any restriction on the distribution of parameters involved in the model. That is the random parameters can follow any possible distribution. In our proposed model, we have considered this situation.

In this paper, we propose a multi-product, single plant production repair model in a particular period. Stochastic parameters appear both in the objective function and in the constraints of the model. We make the proposed model as most general one by imposing no assumptions on the distribution of the stochastic parameters. Therefore, most of the existing methodologies are either not suitable or became extremely complicated to find out an optimal or near optimal solution for such a mathematical model. We propose a Stochastic Simulation (SS) based GA to solve the proposed multiple objective production repair model. It can handle the stochastic objective function and chance constraints in a very simple and efficient manner. As the model consists of more than one objective function, we use the concept of domination to find the best non-dominated solution (Steuer (1986)).

The organization of the paper is as follows: following the introduction, this paper presents the mathematical model of the production repair problem. The technique of stochastic simulation for chance constraints is presented in Section 3. Implementation of the proposed GA algorithm is discussed in Section 4. Computational experience and concluding remarks are presented in Section 5 and 6.

2. A multi-product, single period and single plant production repair model

2.1 Description of the problem

In a production environment, several products are produced according to their demand in the market. When a customer goes to buy a product in the market he generally compares characteristics of comparable models of competing brands. When competing brands are nearly identical, it is very difficult for a buyer to choose a particular product solely on the basis of product characteristics such as product price, special features, financing offered by the manufacturer and so on. In such situations, warranty becomes an important factor for the product choice (Ives et al. (1988), Ritchken (1989)). Another feature of a new product is that each new generation is more complex than the earlier one. Often customers are uncertain about new product performance. Here also warranties play an important role in providing product assurance to customers.

Warranties require the manufacturer to assume responsibility, both financially and operationally when a product goes out of order. According to Gradael and Allenby (1997), this trend is due to simple economics and a growing interest in environmentally concise behavior. Realizing the importance of planning for production of new products as well as for repair products, we consider that a company produces several new products by assembling different components in a particular period. Simultaneously, the company accepts its out of order products for repair only having a valid warranty period.

2.2 Description of terms used in the model

i : Resource index

j : Product index

n : Total number of products

D_j^N : Forecast demand for j^{th} new product in the period, a random variable

I_{j0} : Initial inventory level for j^{th} new product in the period, a deterministic constant

CNP_j Unit production cost (exclusive of labor cost) of j^{th} new product in a period, a deterministic constant

CRP_j Unit repair cost (exclusive of labor cost) of j^{th} repaired product in a period, a random variable

AR_i Amount of type i^{th} resource available, a random variable

RNP_{ij} Amount of type i^{th} resource required to produce an unit of j^{th} new product, a deterministic constant

RPR_{ij} : Amount of type i^{th} resource required to repair an unit of j^{th} product having a valid warranty period, a random variable

RP_j Units of j^{th} products arrive for repair in a period having a valid warranty period, a random variable

MNP_j Man hour required to produce an unit of j^{th} new product, a deterministic constant

MRP_j Manhour required to repair an unit of j^{th} new product, a random variable

ARL Total manhour of regular labor available in a period, a random variable

AOL Total manhour of overtime labor available in a period, a random variable

r: Cost per manhour of regular labor in a period, a deterministic constant

o: Cost per manhour of overtime labor in a period, a deterministic constant

c_j Inventory holding cost per unit of j^{th} new product, a deterministic constant

Decision Variables:

X_j^N : Units of j^{th} new product to be produced in a period

X_j^R : Units of j^{th} product to be repaired in a period

RL: Manhours of regular labor used during a period

OL: Manhours of overtime labor used during a period

I_j Units of j^{th} new product to be left over as inventory in a period

2.3 Assumptions for the model

Before formulating the mathematical model, we assume that

a. For repair, the products arrive randomly.
b. Number of units of products which are accepted for repair in a period must be repaired within the same period.
c. Cost, resources and manhour required to repair a product, arrival of products for repair, resources and manhour availabilities are random variable.

d. The objective function to be maximized is the sum of new and repaired products and to be minimized is the sum of production costs, inventory-holding costs and labor costs.
e. From the past experience it has been seen that around 5 % of demanded new products arrive for repair with a valid warranty in a period.

2.4 Problem Formulation

The objectives of the model consist of maximizing the total number of products and minimizing the total cost. For some known level of significance α_1, α_{2i}, $(i=1,2,...,m)$, α_3, α_{4j}, $(j=1,2,...,n)$, α_5 and α_6, the production repair model is established as –

$$\max : \sum_{j=1}^{n} (X_j^N + X_j^R) \tag{1}$$

$$\max : \sum_{j=1}^{n} (CNP_j \times X_j^N + CRP_j \times X_j^R + c_j I_j) + r \times RL + o \times OL \tag{2}$$

Subject to

$$\Pr\{(X_j^N + I_{j0} - I_j) \le D_j^N\} \ge 1 - \alpha_{1j},\ 0 < \alpha_{1j} < 1,\ j = 1,2,...,n \tag{3}$$

$$\Pr\{\sum_{j=1}^{n} (RNP_{ij} \times X_j^N + RPR_{ij} \times X_j^R) \le AR_i\} \ge 1 - \alpha_{2i},\ 0 < \alpha_{2i} < 1, i = 1,2,...,m \tag{4}$$

$$\Pr\{\sum_{j=1}^{n} (MNP_j \times X_j^N + MRR_j \times X_j^R) \le ARL + AOL\} \ge 1 - \alpha_3,\ 0 < \alpha_3 < 1 \tag{5}$$

$$\Pr(RP_j - X_j^R \le 0) \ge 1 - \alpha_{4j},\ 0 < \alpha_{4j} < 1\ \ j = 1,2,...,n \tag{6}$$

$$\Pr(RL \le ARL) \ge 1 - \alpha_5,\ 0 < \alpha_5 < 1 \tag{7}$$

$$\Pr(OL \le AOL) \ge 1 - \alpha_6,\ 0 < \alpha_6 < 1 \tag{8}$$

$$X_j^N, X_j^R, I_j, RL, OL \ge 0,\ j = 1,2...,n \tag{9}$$

The equation (1) maximizes the total number of products while the equation (2) minimizes the total cost. The two objectives are conflicting in nature. The uncertainty about the demand of a new product in the market, resources required to repair a product within a valid warranty period, man hours required to repair a product within a valid warranty period, availability of man hours, products arrive for repair and resource availabilities bring randomness to equations (3), (4), (5) and (6). Therefore, chance constraints are used to guarantee feasible production plan. Also these constraints help the manager to analyze different and alternative scenario of manufacturing. For example, varying the probabilistic degrees (i.e., the level of significance of the chance constraint) α_{1j} in equations (3), the manager can analyze different marketing policies on production of new products. Equation (7) ensure that the availability of labour hour while equation (8) ensure the overtime hour capacity constraint. Equation (9) is a non-negative constraint.

3. Stochastic simulation for chance constraints

In a stochastic environment, the basic technique of chance constraint programming is to convert the stochastic constraints to their respective deterministic equivalents according to the predetermined confidence level. Let us consider

$$\Pr(X \mid g_i(x, X) \leq 0, j = 1, 2, ..., k\} \geq \alpha \tag{10}$$

where $X = (X_1, X_2, ..., X_n)$ is a n dimensional stochastic vector, and each X_i has a given distribution. For any given *x*, we use the following Monte Carlo simulation technique to estimate the above chance constraints. As discussed in Rubinstein (1981), we generate *N* independent random vectors from their probability distributions.

$$X^{(i)} = (X_1^{(i)}, X_1^{(i)}, ..., X_1^{(i)}), i = 1, 2..., N \tag{11}$$

Let N' be the number of occasions on which following equation satisfies.

$$g_i(x, X^{(i)}) \leq 0, j = 1, 2, ..., k \tag{12}$$

Then by the definition of probability, equation (11) will hold if and only if, $N'/N \geq \alpha$. Therefore, the algorithm for stochastic simulation for chance constraints can be presented as:

Step 1. Set $N' = 0$.

Step 2. Generate *u* according to the distribution function of X_i.

Step 3. Check the value of $g_j(u)$. If $g_j(u) \leq 0$, for $j = 1, 2, ..., k$, then $N' = N' + 1$.

Step 4. Repeat second and third steps *N* times.

Step 5. Find the value of N'/N.

4. SS based GA for the production repair model

With the rapid development of computer technology and software, artificial intelligence technologies like genetic algorithms (GAs) have been found to offer advantages over conventional methods to deal with system modelling and optimization problems, especially for those involving nonlinear and complex mathematical approaches. GA is a combinatorial optimization technique, which searches for an optimal value of a complex objective function by simulation of the biological evolutionary process based on crossover and mutation. It has been successfully applied to a wide variety of problem domains (Goldberg (1989)). The summary of the GA can be presented as-

Step 1: Randomly initialize *psize* number of chromosome according to the initialization process.

Step 2: Check the system constraints by the technique of SS.

Step 3: Apply crossover and mutation scheme as described above to update the chromosomes.

Step 4: For all chromosomes, calculate the value of the objectives.

Step 5: According to the value of the objectives, calculate the fitness value of each chromosome.

Step 6: Select the chromosomes according to the selection process.

Step 7: Repeat **Step 2** to **Step 6**.

Step 8: Report the best chromosome as the optimal solution.

5. Computational Experiments

Suppose that a company produces three new products (i.e., *j*=1,2,3) using two types of resources (i.e., *i* =1,2), namely, $AR_1 \sim U(7000, 8000)$ and $AR_2 \sim U(24000, 25000)$. Also suppose that the chance constraints in the model are satisfied for at least 90% times, available regular labor and available overtime labor are given, respectively, as $ARL \sim N(25000, 200)$ and $AOL \sim N(500, 40)$ and for each of the new products the company will at most allow 30 units to be left out as inventory due to some restrictions. The other relevant data used for the model are presented in the following tables:

Table 1: Data Set-I

J	CRP_j	D_j^N	RRP_{1j}	RRP_{2j}	MRP_j
1	LOGN(2.8,0.02)	U(960,1000)	LOGN(1.2,0.4)	LOGN(2.2,0.4)	LOGN(.4,0.02)
2	LOGN(2.0,1.0)	N(900,8)	LOGN(1.0,0.2)	LOGN(2.1,0.14)	LOGN(.2,0.01)
3	LOGN(3.0,0.4)	U(1050,1100)	LOGN(1.5,0.04)	LOGN(2.4,0.6)	LOGN(0.35,0.22)

Table 2: Data Set-II

j	CNP_j	C_j	I_{j0}	RNP_{1j}	RNP_{2j}	MNP_j	RP_j
1	120	3	30	20	62	8	EXP(50)
2	100	2	25	15	38	5	EXP(45)
3	150	5	35	23	85	7	EXP(54)

The computation work is done using a Pentium - III PC. For the proposed SS based GA, we use the following parameters: the population size is 200, the probability of crossover is 0.8, the probability of mutation is 0.08, the parameter a in the normalized geometric ranking method is 0.005 and the generation number is 40. The time taken to find the solution by SS based GA is 321 seconds. The result obtained is as follows:

Table 3: Obtained solution

X_1^N	X_2^N	X_3^N	X_1^R	X_2^R	X_3^R	I_1	I_2	I_3	RL	OL
998	897	1094	44	42	39	22	25	24	23748	293

The aim of this paper is to introduce chance constraint to deal with stochastic environment in production repair model. The existing GA algorithm can be improved and tested the performance of GA with extensive numerical experiments in future studies.

6. Concluding Remarks

In this work, we have established a mathematical model for some multi-product, single plant and single period production repair problem. We have considered the repair work, which has great importance, of the products having a valid warranty period in this model. Parameters like cost, resources and manhour required to repair a product, arrival of products for repair, resources and manhour availabilities are treated as random variables. Also, there are two objectives in this model. One is maximizing the total number of products and the other is minimizing the total production, inventory holding and manhour cost for the whole production run. Both objectives are conflicting in nature. The proposed SS based GA produced dependable solution within a reasonable time.

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