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MANAGER PREFERENCES MODELLING FOR STOCHASTIC AGGREGATE PLANNING

Abstract

In the Aggregate Production Planning (APP) the manager considers simultaneously conflicting objectives such as total cost, inventories level, workforce fluctuation, and utilization level of the physical facility and equipment. The goals associated with these objectives may be uncertain in nature. The aim of this paper is to develop a Goal Programming (GP) model where the goals and the right-hand sides of constraints are random and normally distributed. The concept of satisfaction functions will be used for modeling the uncertainty as well as to explicitly integrate the manager preferences. The proposed model is applied to APP problem to generate the most satisfying aggregate plan.

Keywords

Aggregate Production Planning; Goal Programming; satisfaction functions.

Introduction

Aggregate Production Planning (APP) deals with matching capacity to forecasted demand. The APP aims to set overall production levels for each family of products to meet fluctuating or uncertain demand in the medium term to set decisions and policies concerning hiring, firing, overtime, backorders, subcontracting and inventory level, and thus determining the appropriate resources that will be used. The APP is one of the most important functions in production and operations management.

Traditionally, the objective of the APP is either to maximize profit or minimize costs and is formulated as a single objective function in linear programming [Hanssmann and Hess, 1960; Bowman, 1956]. Many researchers and practitioners are increasingly aware of the presence of multiple objectives in real life problems [Masud and Hwang, 1980; Baykasoglu, 2001; Leung and Chan, 2009]. The existing APP models assume that the information related to the decision making situation is precise and deterministic. Nevertheless, the demand level, the resources and the costs are not usually known in advance. In such situations, the models mentioned above are no longer realistic. The manager should take into account uncertainty while formulating his/her model. To incorporate uncertainty, some mathematical programming methods such as fuzzy programming and stochastic programming have been developed in the literature.

Wang and Fang [2001] developed a linear programming model to solve the APP where the parameters such as demand, machine time, machine capacity and relevant costs, are fuzzy, in which four objectives are optimized. The fuzzy parameters are represented by trapezoidal fuzzy numbers. Wang and Liang [2005] developed a novel interactive possibilistic linear programming approach for solving the multi-product APP decision problem where cost coefficients in the objective function, forecast demand and capacity are imprecise. This approach attempts to minimize the total cost which is the sum of the production costs and the costs of changes in labor levels over the planning horizon. In the last four decades, many studies have addressed the formulation of risk-averse decision making in the stochastic programming models. Leung and Wu [2004] developed a robust optimization model for stochastic APP by optimizing four objectives under different economic growth scenarios. Leung et al. [2007] proposed a robust optimization model to address a multi-site APP problem in an uncertain environment. Gfrerer and Zapfel [1995] present a multi-period hierarchical production planning model with two planning levels: aggregate and detailed, and with uncertain demand.

In this paper, we will present a stochastic goal programming formulation for APP problem where the goals and some parameters are regarded as random. This model will explicitly integrate the manager's preferences through the concept of satisfaction function developed by Martel and Aouni [1990].

1. The Goal Programming model

The Goal Programming (GP) was originally developed by Charnes and Cooper [1961] and it became the most popular model in multi-objective programming. The standard formulation of the GP model is as follow:

$$\text{Minimize} \quad \sum_{i=1}^{P}\left(\delta_i^+ + \delta_i^-\right)$$

$$\text{Subject to} \quad \sum_{j=1}^{n} c_{ij}x_j + \delta_i^- - \delta_i^+ = g_i \qquad (i = 1, \ldots, p)$$

$$x_j \in S = \left\{ x_j \in R^n / \sum_{j=1}^{n} a_{kj}x_j \begin{pmatrix} \le \\ = \\ \ge \end{pmatrix} b_k, \ x_j \ge 0, \ b_k \in R^m \right\}$$

$$\delta_i^+, \ \delta_i^- \ge 0 \qquad (i = 1, \ldots, p)$$

where g_i represent the aspiration level associated with the objective i, δ_i^+ and δ_i^- indicate the positive and negative deviations of the achievement level from the aspiration level, x_j are decision variables, c_{ij} and a_{kj} are technological coefficients associated with goals and constraints, respectively, and b_k are the limitations of resources. With this formulation, the goal values are considered precise and deterministic. Nevertheless, many uncertain aspiration levels may exist.

2. Stochastic Goal Programming model

The first formulation of Stochastic Goal Programming (SGP) was presented by Contini in 1968 [Contini, 1968]. He considered the goals as random variables with normal distribution. This model is based on the maximization of the probability that the decision belongs to a region encompassing the random goals. In other words, this model tries to obtain a solution which is as close as possible to the random goals. Stancu-Minasian [1984] and Stancu-Minasian and Giurgiutiu [1985] presented a synthesis of methodologies used in multiple objectives programming in a stochastic context. The various approaches proposed use the solution of a deterministic equivalent program. The Chance Constrained Programming (CCP) was introduced by Charnes and Cooper [1959, 1963] to obtain a deterministic program. The main idea of the CCP is to maximize the expected value of the objectives while assuring a certain probability of realization of the various constraints. Some approaches using or referring to SGP are proposed by Ben

Abdelaziz and Mejri [2001], Tozer and Stokes [2002], Bordley and Kirkwood [2004], Sahoo and Biswal [2005]. When time series of probability distributions are not explicitly known, they can be assumed to be defined by fuzzy logic [Ben Abdelaziz and Masri, 2005]. The SGP model formulation proposed by Aouni et al. [2005] explicitly integrates the decision maker's preferences in an uncertain environment. The goals specified by the decision maker $\tilde{g}_i$ are normally distributed with known mean μ_i and variance σ_i^2. This formulation is as follows:

Maximize $\quad Z = \sum_{i=1}^{p} \left(w_i^+ F_i^+(\delta_i^+) + w_i^- F_i^-(\delta_i^-) \right).$

Subject to: $\quad \sum_{j=1}^{n} c_{ij} x_j - \delta_i^+ + \delta_i^- = \mu_i; \qquad (i = 1, \dots, p),$

$x_j \in S,$

$\delta_i^+ \text{ and } \delta_i^- \leq \alpha_{iv} \qquad (i = 1, \dots, p),$

$\delta_i^+, \delta_i^- \text{ and } x_j \geq 0 \qquad (i = 1, \dots, p), \quad (j = 1, \dots, n).$

where $F_i(\delta_i)$ are the satisfaction functions associated with positive and negative deviations (δ_i^+, δ_i^-) as presented in Figure 1. The coefficients w_i^+ and w_i^- express the relative importance of the positive and negative deviations, respectively; α_{id} is the indifference threshold; α_{i0} is the null satisfaction threshold and α_{iv} is the veto threshold.

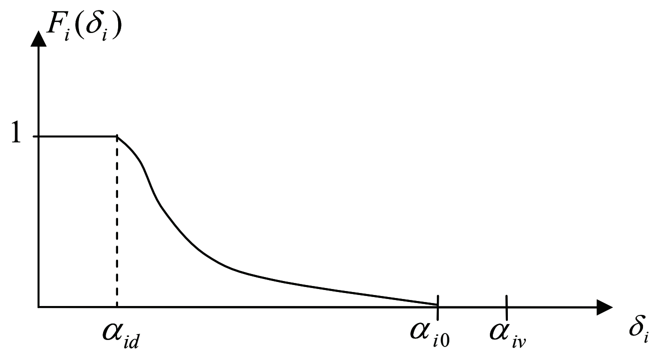

Figure 1. General form of the satisfaction function

In the following section, we extend the SGP model formulation proposed by Aouni et al. [2005] to take into account the randomness goals and the right- -hand sides of the constraints.

3. The proposed model in an uncertain environment

In this section, we begin by introducing the following goal programming model with uncertain goals and the right-hand sides of the constraints.

$$\textit{Optimize} \sum_{j=1}^{n} c_{ij} x_j \qquad (i = 1, \dots, p).$$

Subject to

$$\sum_{j=1}^{n} a_{kj} x_j \le \tilde{b}_k \qquad (k = 1, \dots, m_1),$$

$$\sum_{j=1}^{n} a_{kj} x_j \le b_k \qquad (k = m_1 + 1, \dots, m).$$

$$x_j \ge 0$$

Let $\tilde{g}_i$ be the uncertain aspiration levels for the i^{th} objective function $\sum_{j=1}^{n} c_{ij} x_j$. $\sum_{j=1}^{n} a_{kj} x_j \le (=, \ge)\, \tilde{b}_k$ indicates that the k^{th} uncertain right-hand side parameter is greater than or equal to (equal or less than or equal to) $\sum_{j=1}^{n} a_{kj} x_j$. The other variables are defined as in standard GP. We assume that the goals and the right-hand sides of the constraints are uncertain variables with a normal distribution (μ_i, μ_k, σ_i^2 and σ_k^2 are known): $\tilde{g}_i \in N(\mu_i, \sigma_i^2)$ and $\tilde{b}_k \in N(\mu_k, \sigma_k^2)$. Therefore, we have: $P\left(\tilde{g}_i = \sum_{j=1}^{n} c_{ij} x_j\right)$ are equivalent to

$$P\left[\left((\tilde{g}_i - \mu_i)/\sigma_i\right) = \left(\left(\sum_{j=1}^{n} c_{ij} x_j - \mu_i\right)/\sigma_i\right)\right], \text{ where } \left((\tilde{g}_i - \mu_i)/\sigma_i\right) \in N(0,1)$$

$(\mathrm{i}=1,\ldots,\mathrm{p})$ and $P\left(\tilde{b}_k \geq \sum_{j=1}^{n} a_{kj}x_j\right)$ are equivalent to

$$P\left[\left((\tilde{b}_k-\mu_k)/\sigma_k\right)\geq\left(\left(\sum_{j=1}^{n}a_{kj}x_j-\mu_k\right)/\sigma_k\right)\right] \quad (k=1,\ldots,m_1), \text{ where } \left((\tilde{b}_k-\mu_k)/\sigma_k\right)\in N(0,1).$$

By introducing the satisfaction functions, the goal programming model in stochastic environment can be formulated as follows:

$$Maximize \ \sum_{i=1}^{p} w_i\left(F_i^+(\delta_i^+)+F_i^-(\delta_i^-)\right)+\sum_{k=1}^{m_1} w_k F_k^+(\gamma_k^+).$$

Subject to:

Goal constraints

$$\sum_{j=1}^{n} c_{ij}x_j-\delta_i^+ +\delta_i^- = \mu_i \qquad (i=1,\ldots,p),$$

$$\sum_{j=1}^{n} a_{kj}x_j-\gamma_k^+ +\gamma_k^- = \mu_k \qquad (k=1,\ldots,m_1).$$

System constraints

$$\sum_{j=1}^{n} a_{kj}x_j \leq b_k \qquad (k=m_1+1,\ldots,m),$$

$$x_j \geq 0 \qquad (j=1,\ldots,n),$$

$$\delta_i^+ \text{ and } \delta_i^- \leq \alpha_{iv},\ \gamma_k^+ \text{ and } \gamma_k^- \leq \alpha_{kv},$$

$$\delta_i^+,\delta_i^-,\gamma_k^+,\gamma_k^- \geq 0.$$

where:

δ_i^+,γ_k^+ indicate the over achievement of the goals $\tilde{g}_i$ and $\tilde{b}_k$ and δ_i^-,γ_k^- indicates the under achievement of these goals. α_{iv} and α_{kv} represent the veto thresholds.

The formulation proposed seeks not only to determine a solution that the probabilities $\tilde{g}_i \in (\mu_i-\varepsilon_i,\mu_i+\varepsilon_i)$ and $\tilde{b}_k \in (\mu_k+\varepsilon_k)$ are maximized (where ε_i and ε_k are very small positive numbers), but also to take into account the manager's preferences regarding the deviations from the target values of each objective. The threshold values of the satisfaction functions depend on the manager's appreciation of the deviations σ_i^2 and σ_k^2 . The indifference thresholds for each goal are greater than or equal to ε_i and ε_k .

4. APP model formulation

We illustrate the stochastic goal programming model proposed for an aggregate production planning problem where the goals associated with the objectives and market demands for each period of the planning horizon are uncertain and normally distributed. The objective functions of this decision problem are to minimize the total production cost, the changes in workforce level and the total inventory and backorder cost.

In the following, the parameters and the variables for the model are defined. Mathematical formulation of the model proposed, including various goal constraints related to the respective goals, system constraints, and the achievement function are also described.

4.1. Notations

Parameters and constants

T: Planning horizon or number of periods;
CP_t: Production cost per unit of regular time in period t;
CO_t: Production cost per unit of overtime in period t;
CR_t: Labor cost in period t;
CI_t^+ : Inventory cost per unit in period t;
CI_t^-: Backorder cost per unit in period t;
CH_t: Cost to hire one worker in period t;
CF_t: Cost to lay off one worker in period t;
$\widetilde{D}_t$: Forecasted demand in period t;
i_t : Labor time in period t (man hour/unit);
a: Regular working hours per worker;
b_t: Fraction of working hours available for overtime production.

Decision variables

P_t: Regular time production in period t;
O_t: Overtime production in period t;
W_t: Workforce level in period t;
I_t^+: Inventory level at the beginning of period t;
I_t^-: Backorder level at the beginning of period t;
H_t: Number of workers hired in period t;
F_t: Number of workers laid off in period t.

4.2. Goal constraints and objective functions

Goal 1: *Total production cost goal.*
The total production cost goal constraint is illustrated below; it takes into account regular time production costs, overtime production costs, and the labor cost at regular time.

$$\sum_{t=1}^{T}\left(CP_t.P_t + CO_t.O_t + CR_t.W_t\right) - \delta_1^+ + \delta_1^- = \mu_{g_1}.$$

Parameter μ_{g_1} denotes the mean production cost. A positive deviational variable δ_1^+, represents the over achievement of the goal $\tilde{g}_1$ and a negative deviational variable δ_1^-, represents the under achievement of this goal. This gives $\delta_1^+.\delta_1^- = 0$.

Goal 2: *The changes in workforce level goal.*
This objective includes the hiring cost and the lay-off cost. The goal constraint is formulated below.

$$\sum_{t=1}^{T}\left(CH_t.H_t + CF_t.F_t\right) - \delta_2^+ + \delta_2^- = \mu_{g_2}.$$

Parameter μ_{g_2} denotes the mean change in workforce level. A positive deviational variable δ_2^+, represents the over achievement of the goal $\tilde{g}_2$ and a negative deviational variable δ_2^-, represents the under achievement of this goal. This gives $\delta_2^+.\delta_2^- = 0$.

Goal 3: *Total inventory and backorder cost goal.*

This goal includes two components: the inventory carrying cost and the backorder cost. The goal constraint is formulated below.

$$\sum_{t=1}^{T}\left(CI_t^{+}.I_t^{+}+CI_t^{-}.I_t^{-}\right)-\delta_3^{+}+\delta_3^{-}=\mu_{g_3}.$$

Parameter μ_{g_3} denotes the mean cost of the total inventory and backorder. A positive deviational variable δ_3^{+}, represents the over achievement of the goal $\widetilde{g}_3$ and a negative deviational variable δ_3^{-}, represents the under achievement of this goal. This gives $\delta_3^{+}.\delta_3^{-}=0.$

Goal 4: *Demand goal.*

The demand goal constraint is illustrated as follows: the sum of regular and overtime production, inventory level, and backorder level should equal approximately the market demand.

$$I_{t-1}^{+}-I_{t-1}^{-}+P_t+O_t-I_t^{+}+I_t^{-}-\rho_t^{+}+\rho_t^{-}=\mu_{g4} \qquad (t=1,\ldots,\ T).$$

Parameter μ_{g_4} denotes the mean demand. A positive deviational variable ρ_t^{+}, represents the over achievement of the goal $\widetilde{g}_4$ and a negative deviational variable ρ_t^{-}, represents the under achievement of this goal. This gives $\rho_t^{+}.\rho_t^{-}=0 \ \ (t=1,\ldots,\ T)$.

By introducing the satisfaction functions, the multi-objective aggregate production planning problem in stochastic environment is formulated as follows:

$$Maximize \quad Z=\sum_{i=1}^{3}w_iF_i^{+}\left(\delta_i^{+}\right)+\sum_{t=1}^{T}\left(F_t^{+}\left(\rho_t^{+}\right)+F_t^{-}\left(\rho_t^{-}\right)\right).$$

4.3. System constraints

$$\mathrm{W_t}=\mathrm{W_{t-1}}+\mathrm{H_t}-\mathrm{F_t} \qquad (t=1,\ldots,\ T), \tag{1}$$

$$\mathrm{i_tP_t}\le \mathrm{aW_t} \qquad (t=1,\ldots,\ T), \tag{2}$$

$$\mathrm{i_tO_t}\le \mathrm{a\,b_tW_t} \qquad (t=1,\ldots,\ T), \tag{3}$$

$$\delta_i^+ \text{ and } \delta_i^- \leq \alpha_{iv} \qquad (i=1, \dots, 3), \tag{4}$$

$$\rho_t^+ \text{ and } \rho_t^- \leq \alpha_{tv} \qquad (t=1, \dots, T) \tag{5}$$

Constraints (1) ensure that the available workforce in any period equals workforce in the previous period plus the change of workforce in the current period (hiring minus firing). Constraints (2) ensure that the labor times for manufacturing the products during regular time should be limited to the available regular time workforce. Constraints (3) limit the fraction of workforce available for overtime production. Finally, the two kinds of deviations should not exceed the veto threshold (4) and (5).

5. Computational results

In this section, the same data set as presented by Gen et al. [1992] is used to illustrate the proposed stochastic goal programming model for the aggregate production planning problem. A six period's planning horizon with probabilistic demands is considered. The market demands for the five last years (N-1 to N-5) are presented in Table 1. Our objective is to generate a production plan for year N where the goals values are random and where the decision-maker's preferences are explicitly integrated. Table 2 shows the random goals. Table 3 shows the different costs (production, inventory, backorder, labor, hiring and firing). The number of labor hours needed for each unit of production is three and the regular work day is eight man-hour per day. The initial workforce is 100 workers (man-day). The initial inventory and backorder are nil (equal to zero). Overtime production is limited to no more than 14% of regular time production.

Table 1

Market demands per year

	1	**2**	**3**	**4**	**5**	**6**
N-1	190	173	250	200	255	*310*
N-2	250	156	288	240	300	*270*
N-3	196	232	310	280	210	*210*
N-4	240	168	344	190	284	*216*
N-5	220	220	309	240	350	*280*
Mean values	***220***	***190***	***300***	***230***	***280***	***257***

Table 2

Goals per year

	Total production cost	The changes in workforce level cost	*Total inventory and backorder cost*
N-1	57 715	40	*16*
N-2	49 400	70	*8*
N-3	60 000	140	*0*
N-4	61 885	110	*8*
N-5	56 000	30	*8*
Mean values	***57 000***	***78***	***8***

Table 3

Production costs

Production cost other than labor cost	$16 per unit
Labor cost at regular time	$60 per worker
Hiring cost	$30 per worker
Firing cost	$40 per worker
Inventory carrying cost	$2 per unit
Backorder cost	$10 per unit
Overtime production cost	$49 per unit

For the above three objectives we have used the satisfaction function of type III where the target's mean and the thresholds are summarized in Table 4. For the market demands objective, we use a satisfaction function of type II and the thresholds for the positive and negative deviations are the same during the planning horizon $\left(\alpha_{td}^{+} = \alpha_{td}^{-} = 20 \text{ and } \alpha_{tv}^{+} = \alpha_{tv}^{-} = 30\right)$. The shape of these functions is as follows (Figure 2).

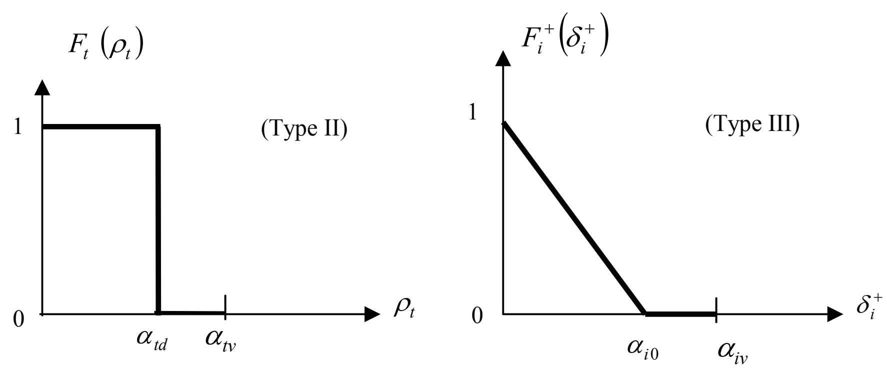

Figure 2. Shape of satisfaction function

The relative weights associated with the four goals are equal.

Table 4

Set of targets and satisfaction thresholds

Objectives	Target's mean μ_i	Nil-satisfaction threshold	Veto threshold
Total production cost	57 000	3000	4000
The changes in workforce level cost	78	30	40
Total inventory and backorder cost	8	16	20

The satisfaction functions are used to explicitly incorporate the manager's preferences in a stochastic environment. The equivalent representation of the various satisfaction functions requires the introduction of binary variables. The obtained model is non linear. The linearization procedure developed by Oral and Kettani [1992] and modified by Aouni [1996] is used to generate the linear equivalent formulation of the stochastic APP problem. The software package Lindo 6.1 is used to solve the mathematical programming problem.

Using the above data, the aggregate production plan is performed and the results are given in Table 5. The satisfaction level of the objective function is 98%. In fact, the achievement levels of the objectives are: total production cost is $57 223, the change in workforce level cost is $80, the total inventory and backorder cost is $24 and finally the values of market demand for the planning horizon are respectively: 200, 170, 280, 210, 260 and 237 units. Therefore, the goal values of market demand reached are within the indifference region. The regular time production for period 2 exceeds the market demand by 12 units. The production level reaches the peak during the third period.

Table 5

Production plan

Period	1	2	3	4	5	6
Regular time production	200	182	261	210	260	237
Overtime production	0	0	7	0	0	0
Inventory level	0	12	0	0	0	0
Backorder level	0	0	0	0	0	0
Workforce level	98	98	98	98	98	98
Workers hired	0	0	0	0	0	0
Workers layoff	2	0	0	0	0	0

Conclusion

In this paper, we have proposed a stochastic goal programming model for solving an aggregate planning problem where the concept of satisfaction function was used to integrate explicitly the manager's preferences.

The model proposed has been illustrated through a hypothetical example of aggregate production planning problem. This model can be applied to large--scale production planning. Moreover, the model proposed can be easily based on information technology tools.

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