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Supply Chain Management through the Stochastic Goal Programming Model

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Abstract: Supply Chain (SC) design problems are often characterized with uncertainty related to the decision-making parameters. The Stochastic Goal Programming (SGP) was one of the aggregating procedures proposed to solve the SC problems. However, the SGP does not integrate explicitly the Decision-Maker's preferences. The aim of this paper is to utilize the Chance Constrained Programming and the Satisfaction Function concept to formulate strategic and tactical decisions within the SC while demand, supply and total cost are random variables.

Keywords: Supply Chain, Stochastic Goal Programming, Chance Constrained Programming, Manager's Preferences, Satisfaction Functions.

1. Introduction

Supply Chain Management (SCM) includes planning and management of all activities involved in a Supply Chain (SC) which consists of the entities such as suppliers, manufacturers, warehouses, retailers, transporters, and customers. The main objective of the SCM is to increase the organization's profit through maximizing the efficiency of the SC. Mathematical modeling is an effective, inexpensive and comprehensive approach to measure the efficiency of the SC under different input conditions. While most of the efforts for modeling and optimization of the SC design are based on precise and deterministic approach, real SC design problems are characterized with uncertainty especially when considering elements that are beyond the scope of the company (Azaron *et al.*, 2010). The Fuzzy Goal Programming (FGP), the GP with Intervals (GPI) and the Stochastic Goal Programming (SGP) are the three variants of the GP used to address the uncertainty of the goal values (Cherif *et al.*, 2008). Martel and Aouni (1998) underline that FGP and GPI generally deal with situations that the membership and penalty functions are linear and symmetric and favor the central value of the goal values. They also argue that both the FGP and the GPI models emphasize more on the imprecision of the goals rather than Decision-Maker's (DM) preference modeling. Aouni *et al.* (2005) applied the satisfaction function concept introduced by Martel and Aouni (1990) into the SGP to address the above mentioned shortcomings. The advantage of satisfaction function comparatively to the concepts of penalty function (regret function) and membership function is that it does not need to be necessarily symmetric and linear (Cherif *et al.*, 2008).

The SGP has been applied in many fields; however the literature review shows that the SGP and the satisfaction functions have not been applied together for modeling the SC problems under uncertainty. In this paper, the SGP and the satisfaction function are applied to formulate a SC design problem where the goals for demand, supply and total cost are stochastic variables with Normal probability distribution.

The paper contains nine sections. In sections 2 and 3, we will briefly review the existing literature related to the Supply Chain Management and the Goal Programming model, and then a general formulation of the Stochastic Goal Programming is presented at section 4. In section 5, we will introduce the general formulation of the Supply Chain. In section 6, the Goal Programming model will be utilized to formulate the Supply Chain problem. The Stochastic Goal Programming model and the satisfaction functions will be combined together in section 7 for formulating the Supply Chain within an uncertain decision-making environment. Finally, in section 8 we will present a numerical example that illustrates well the proposed model. This example will be solved through LINGO software version 11. Section 9 includes some concluding remarks.

2. Supply Chain Management

A typical Supply Chain consists of different entities including Customer, Retailer, Distributor, Manufacturer and

Supplier. According to the Council of Supply Chain Management Professionals (CSCMP), the Supply Chain Management (SCM) is planning and management of all activities involved in sourcing and procurement, conversion, and logistics as well as coordination and collaboration with the entities. The CSCMP describes the primary responsibility of the SCM as integration of the major business functions and business processes within and across the entities into a solid and high performing business model.

Based on the decisions frequency and their time frame of effectiveness, Chopra and Meindl (2001) divided the decisions involved in SCM into three categories of SC strategy (design), SC planning and SC operation. The strategic decisions address the location and capacity of the manufacturing facilities and warehouses, products to be produced or stored at different locations, transportation mode along different shipping legs and type of information system. In planning phase companies define the operating policies that manage short-term operations, within the constraints established by the configuration set in the strategy phase. Planning usually starts with a forecast of the coming year of demand in different markets and includes deciding about which market will be supplied from which locations, the planned buildup of inventories, the subcontracting of production, the replenishment and inventory policies, the policies regarding backup locations in case of stock out and the timing and size of marketing promotions. In operation phase the decisions associated with individual orders, and the goal is to exploit the reduction of uncertainty and optimize performance within the constraint defined by the configuration and planning policies.

In order to optimize the SC, the firm should ensure that the entities are properly located, the capacity of the different entities is enough and the structure of SC is in line with the SC strategy. Mathematical modeling is an effective, inexpensive and comprehensive method for optimization of the performance of SC under different input conditions. Following a comprehensive review of the literature, Mula *et al*. (2009) listed the major mathematical programming models applied in SC related literature as: Linear Programming, Mixed Integer/ Integer Linear Programming, Non Linear Programming, Multi Objective Programming, Fuzzy Mathematical Programming, Stochastic Programming, Heuristics Algorithms and Meta-heuristics, and hybrid models. According to the review, linear programming-based modeling is the most frequently used approach in the literature. The review also pointed out that the research works have mainly focused on optimization of tactical (planning) rather than strategic or operational decisions.

3. Goal Programming and Supply Chain Management

The GP is one of the most popular mathematical programming models for solving multi objective problems. The main objective of the GP is to minimize the deviations among the achievement and the aspirations levels of the objectives (Aouni *et al.* 2005). Since its introduction by Charnes *et al.* in 1955, the GP model application has stretched to different areas such as water management, waste management, accounting, stock management, marketing, quality control, human resource management, telecommunication, agriculture, forestry, aviation as well as Supply Chain Management (Aouni and Kettani 2001).

The SCM tries to harmonize the customer needs with materials flow from suppliers, to balance normally conflicting objectives of low unit cost, low inventory, low rejected rate, high customer service, and high flexibility (Stevens1989, Kumar *et al.* 2004). The issues of SCM have been extensively studied by the researchers, but most of the related research works have focused on a single component such as procurement, production, transportation, warehouses or scheduling, rather than the whole system as a single supply chain (Sabri and Beamon 2000). For example Wang *et al.* (2004) integrated Analytic Hierarchy Process (AHP) and Preemptive Goal Programming (PGP) to develop a multi-criteria decision-making methodology for supplier selection. Azadeh *et al*. (2010) integrated GP with computer simulation and Design of Experiment to solve a multi objective job shop scheduling problem. Leung and Chan (2009) developed a preemptive GP model to solve an aggregate production planning problem. Leung and lung Ng (2007) developed a PGP model to solve aggregate production planning for perishable products. Li *et al.* (2006) proposed a GP approach to formulate an Earliness–Tardiness Production Planning problem. Taylor and Anderson (1979) developed a GP algorithm to coordinate and integrate production and marketing and address conflicts involved in marketing-production planning decisions. Forza *et al.* (2005) applied GP approach to identify and formalize the potential tradeoffs among decisions across product design, process design, and supply chain design. Ho *et al*. (2008) devised an integrated multiple criteria decision making approach to optimize the facility location-allocation problem in the contemporary customer-driven Supply Chain. Finally, Zhou *et al*. (2000) applied GP to exert optimization on the whole supply chain from procurement to distribution for Continuous Process Industry. Their research is among the few that have considered the whole components as a single supply chain.

While most of the efforts for modeling and optimization of SC design are based on precise and deterministic approach, in practice SC design problem are characterized with uncertainty especially when considering elements are beyond the scope of the company (Azaron *et al.*, 2010). The imprecision within SCM normally relates to the goal and constraint target values (Liang, 2009; Lotfi and Torabi, 2011; Özcan and Toklu, 2009), but could also relate to other aspects of the goal program such as the parameters (Sinha *et al*. ,1988; Cherif *et al*., 2008), and the priority structure(Aköz and Petrovic, 2007).

The FGP and SGP are effective and comprehensive approaches to optimize the performance of SC under imprecise information condition and have been widely applied in SC related literature. However, Ignizio (1982) and Martel and Aouni (1998) highlighted some issues regarding the analytical form of the membership functions in the FGP. They underlined that FGP favors central values of the intervals and generally deal with situations that the membership are linear and symmetric. Besides, since the fuzzy goal values are expressed through intervals, the DM is assumed neutral regarding the solutions within the limits defining the interval (Cherif *et al.,* 2008). Moreover, membership function does not explicitly incorporate the DM's preference into the problem formulation, which is expressed by the DM's satisfaction regarding the deviation of the achievement level from the aspired level (Martel and Aouni, 1996). In addition, in FGP it is assumed that the available information for decision making fuzzy which does not address the uncertainty that may be involved in decision making process due to stochastic information. The SGP variant can tackle this issue. In the following section SGP is discussed and it is explained how SGP and the satisfaction function can address the shortcomings of FGP model.

4. Stochastic Goal Programming

The first model of the Stochastic Goal Programming (SGP) was developed by Contini (1968). The model maximizes the probability that the consequence of the decision falls within a certain range around the goal. The most popular technique for solving the SGP model is the Chance Constrained Programming (CCP) developed by Charnes and Cooper (1952, 1959, 1963). Although the literature review shows absence of application of the Chance Constrained Goal Programming model in the SCM, it confirms wide employment of the concept in other applications. For example Bravo and Gonzalez (2009) applied the SGP to optimize allocation of surface water among farmers to fulfill farm management and environmental impact goals. Bhattacharya (2009) proposed a model based on the CCP to maximize the reach to the desired section of people through optimizing number and allocation of budget assigned to different advertising media. Liu (1996) developed a general formulation of the Dependent-Chance Goal Programming (DCGP) in a complex stochastic system and presented its application in water allocation and supply example. Ben Abdelaziz and Sameh (2001) utilized the SGP to find appropriate releases from various water reservoirs in the system in order to satisfy multiple conflicting objectives, such as satisfaction of demands and minimization of the pumping cost. Yang and Feng (2007) incorporated expected value GP, CCP and DCGP into their approach to solve a bi-criteria solid transportation problem. Min and Melachrinoudis (1996) applied the CCP approach to develop a multiple-period, multiple-plant, multiple-objective, and stochastic location model for formulating location strategies. The CCP attempts to maximize the expected value of the objectives for given probability of realization of the different constraints. Depending on the treatment of the constraints two approaches for the CCP can be adopted which are the unconditional CCP and the joint CCP. In the unconditional CCP the decision maker is interested in realization of the constraints independent from each other, but in the joint CCP the joint realization of the constraints is sought. The following programs demonstrate the general formulation of both forms.

The unconditional CCP:

Program 1-1: Max E ($f(\underline{x})$)

s.t. $P\left[\sum_{j=1}^{n} a_{ij}x_j \le \tilde{b_i}\right] = \alpha_i \;\; \forall i \in I$

$\underline{x} \geq 0$

where α_i ($\alpha_i \in [0 , 1]$) is the threshold values that are defined by the decision maker and ***I*** is the number of the objectives.

The joint CCP:

Program 1-2: Max E ($f(\underline{x})$)

s.t. $P\left[\sum_{j=1}^{n} a_j x_j \le \tilde{b}\right] = \alpha,$

$\underline{x} \geq 0.$

Aouni *et al.* (2005) applied the unconditional CCP to reformulate the following program with stochastic goals into a deterministic format:

Program 1-3: Min $z = \sum_{i=1}^{n}(\tilde{\delta}_i^{+} + \tilde{\delta}_i^{-})$

s.t. $\sum_{j=1}^{n} a_{ij}x_j - \tilde{\delta}_i^{+} + \tilde{\delta}_i^{-} = \tilde{g}_i \quad \forall i \in I,$

$\tilde{\delta}_i^{+}, \tilde{\delta}_i^{-} \geq 0,$

where $\tilde{g}_i \in N(\mu_i; \sigma_i^2)$ and μ_i and σ_i^2 $(\forall i \in I)$ are known

Since $P(\tilde{g}_i \cong \sum_{i=1}^{l} a_{ij}x_j)$ is equivalent to $P[(\frac{\tilde{g}_i - \mu_i}{\sigma_i}) \cong ((\sum_{i=1}^{l} a_{ij}x_j - \mu_i)/\sigma_i)]$, where $\left(\frac{\tilde{g}_i - \mu_i}{\sigma_i}\right) \in N(0; 1)$,we can look at minimizing $\sum_{i=1}^{l} a_{ij}x_j - \mu_i$. Therefore program 1-3 can be reformulated into the following deterministic equivalent program:

Program 1-4: Min $z = \sum_{i=1}^{n}(\delta_i^{+} + \delta_i^{-})$

s.t. $\sum_{j=1}^{n} a_{ij}x_j - \delta_i^{+} + \delta_i^{-} = \mu_i \quad \forall i \in I$

$\delta_i^{+}, \delta_i^{-} \geq 0 \; \forall i \in I$

In order to incorporate the decision maker's (DM) preference into the model, Martel and Aouni (1990), introduced the concept of satisfaction functions which allows the DM to express explicitly his/her satisfaction regarding the deviations of the achievement level from the aspired level goals. The general shape of the satisfaction functions has been depicted below:

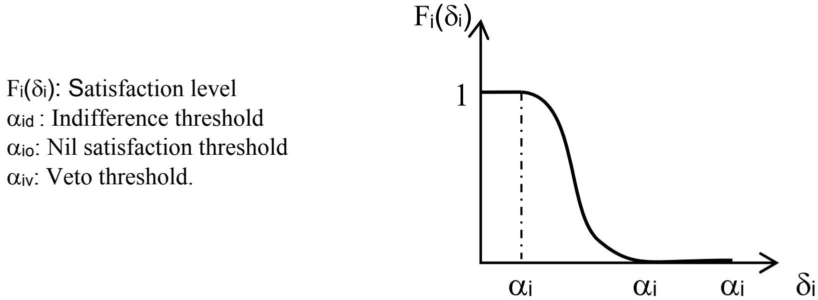

Fig. 1. General shape of the satisfaction functions

where $F_i(\delta_i)$ is the satisfaction level corresponding to deviation δ_i; α_{id} represents the indifference threshold; α_{io} represents the nil satisfaction threshold; α_{iv} represents the veto threshold.

According to this model, when the deviations δ_i is within $[0, \alpha_{id}]$, the decision maker is fully satisfied and the satisfaction level is 1. As the deviation exceeds α_{id}, the satisfaction level falls until reaches zero at α_{io}. If the deviation exceeds this level, the decision maker may still consider the solution. But the solution is rejected if it exceeds veto threshold α_{iv}.

By using the concept of satisfaction functions, Aouni *et al.* (2005) reformulated program 1-4 as:

Program 1-5: Max $\quad z = \sum_{i=1}^{n} \omega_i \left(F_i^+(\delta_i^+) + F_i^-(\delta_i^-)\right)$

s.t. $\quad \sum_{j=1}^{n} a_{ij}x_j - \delta_i^+ + \delta_i^- = \mu_i \qquad (\forall i \in I)$

$x \in X$

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

$\delta_i^+, \delta_i^- \leq \alpha_{iv} \qquad (\forall i \in I)$

With application of Program 1-5 we can easily formulate the SGP model of the SC, but before that we first need to represent the general formulation of the SC. In the following sections the general formulation and GP model of SC are represented.

5. General Formulation of Supply Chain

A typical Supply Chain network usually has several stages including suppliers, plants, warehouses, and markets. There may also be other middle facilities such as consolidation centers or transit points. Santoso *et al.* (2005) formulated a deterministic mathematical model for Supply Chain design problem that is described below.

Consider a Supply Chain network G=(N, A) which consists of the set of nodes N and the set of arches A. The set N comprises the set of suppliers S, the set of potential processing facilities P, and the set of customer centers C, *i.e.*, N=S∪P∪C. The processing facilities consist of production centers M and warehouses W, *i.e.*, P=M∪W, while K is the set of products distributed through the SC.

The strategic decisions involve deciding which of the processing centers to build and the tactical decisions include routing the stream of each product $k \in$ K from the suppliers to the customers.
A binary variable y_i is associated to strategic decisions where y_i equal to 1 if the processing facility i is built, and 0 otherwise. x_{ij}^k denotes the flow of product k from node i to node j in the network where $(ij) \in$ A and z_j^k indicate shortfall of product k at customer center $j \in$C when demand cannot be met. e_j^k represent capacity expansion at node $j \in$P when the capacity should be increased.

A deterministic mathematical model for this SC design problem can be formulated as:

Program 2-1: Min $\displaystyle\sum_{i \in P} c_i y_i + \sum_{k \in K} \sum_{(ij) \in A} q_{ij}^k x_{ij}^k + \sum_{k \in K} \sum_{j \in C} h_j^k z_j^k + \sum_{k \in K} \sum_{j \in C} f_j^k e_j^k \qquad$ 2a

s.t.

$$\sum_{i \in N} x_{ij}^k - \sum_{l \in N} x_{il}^k = 0 \qquad \forall j \in P, \quad \forall k \in K \qquad \text{2b}$$

$$\sum_{i \in N} x_{ij}^k + z_j^k \geq d_j^k \qquad \forall j \in C, \quad \forall k \in K \qquad \text{2c}$$

$$\sum_{j \in N} x_{ij}^k \leq s_i^k \qquad \forall i \in S, \quad \forall k \in K \qquad \text{2d}$$

$$\sum_{k\in K} r_j^k (\sum_{i\in N} x_{ij}^k) \le m_j^k y_j^k + \sum_{k\in K} e_j^k \quad \forall j \in P, \quad \forall k \in K, \quad \forall (ij) \in A \tag{2d}$$

$$\sum_{k\in K} e_j^k \le \sum_{k\in K} y_j^k o_j^k \quad \forall j \in P, \quad \forall k \in K \tag{2f}$$

$$y \in Y \subseteq \{0,1\}^{|P|} \tag{2g}$$

$$x_{ij}^k \ge 0 \tag{2h}$$

$$r_j^k \ge 0 \tag{2i}$$

$$z_j^k \ge 0 \tag{2j}$$

where c_j, d_j^k, s_i^k, r_j^k, m_j^k and o_j^k denote investment cost of building processing center j ($j\in$P), demand of product k at node j ($j\in$C), supply of product k at node i ($i\in$S), per unit processing requirement for product k at node j ($j\in$P), capacity of facility j ($j\in$P) for product k, and expansion limit of node j ($j\in$P) for product k, respectively.

In program 2-1, the objective function (2a) consists of minimizing the sum of investment, production/ transportation, shortage and expansion costs. Constraint (2b) enforces the flow conservation of product k across each processing node j. Constraint (2c) requires that the total flow of product k to a customer node j plus shortfall exceed the demand d_j^k at that node. Constraint (2d) requires that the total flow of product k from a supplier node i stay below the supply s_i^k at that node. Constraints (2e) and (2f) enforce capacity and expansion constraints of the processing nodes, respectively. Constraint (2g) enforces the binary nature of the configuration decisions for the processing facilities.

6. Goal Programming Modeling of the Supply Chain

A generic GP model can be formulated as:

Program 3-1:

Min $\quad \Sigma\, (\delta_i^+ + \delta_i^-)$

s.t. $\quad f_i(x) - \delta_i^+ + \delta_i^- = g_i \quad (\forall i \in \mathrm{I})$ where I objectives are considered

$\quad x \in \mathrm{X} \subset \mathrm{R}^n$

$\quad \delta_i^+, \ \delta_i^- \ge 0$

Where g_i represents the aspiration level (goal) associated with the objective $f_i(x)$, and X denotes the set of the feasible solutions. The variables δ_i^+ and δ_i^- designate the positive and negative deviations of the achievement level $f_i(x)$ from aspirated level g_i.

The GP can be utilized to formulate the SC problem where g_c, g_d and g_s denote goals for total cost, demand and supply and $\delta_c^+, \delta_n^+ + \delta_n^-, \delta_d^-, \ \delta_s^+, \delta_m^+$ and δ_e^+ designate the unwanted deviation variables associated to total investment cost, flow conservation in each processing node j, total demand, total supply, capacity limit and expansion limit, respectively.

Program 3-2: $\text{Min}\,\{\delta_c^+,\ \delta_n^- + \delta_n^+,\ \delta_d^-,\ \delta_s^+,\ \delta_m^+, \delta_e^+\}$ 3a'

s.t.

$$\sum_{i\in P} c_i y_i + \sum_{k\in K}\sum_{(ij)\in A} q_{ij}^k x_{ij}^k + \sum_{k\in K}\sum_{j\in C} h_j^k z_j^k + \sum_{k\in K}\sum_{j\in C} f_j^k e_j^k + \delta_c^- - \delta_c^+ = g_c \tag{3a}$$

$$\sum_{i\in N} x_{ij}^k - \sum_{l\in N} x_{il}^k + \delta_n^- - \delta_n^+ = 0 \quad \forall j \in P, \quad \forall k \in K \tag{3b}$$

$$\sum_{i\in N} x_{ij}^k + z_j^k + \delta_{dj}^- - \delta_{dj}^+ = g_{dj}^k \quad \forall j \in C, \quad \forall k \in K \tag{3c}$$

$$\sum_{j\in N} x_{ij}^k + \delta_{si}^- - \delta_{si}^+ = g_{si}^k \quad \forall i \in S, \quad \forall k \in K \tag{3d}$$

$$\sum_{k\in K} r_j^k (\sum_{i\in N} x_{ij}^k) - \sum_{k\in K} m_j^k y_j^k - \sum_{k\in K} e_j^k + \delta_{mj}^- - \delta_{mj}^+ = 0 \quad \forall j \in P, \quad \forall k \in K, \quad \forall (ij) \in A \tag{3e}$$

$$\sum_{k\in K} e_j^k - \sum_{k\in K} y_j^k o_j^k + \delta_{ej}^- - \delta_{ej}^+ = 0 \quad \forall j \in P, \quad \forall k \in K \tag{3f}$$

$$y \in Y \subseteq \{0,1\}^{|P|} \quad \text{3g}$$
$$x_{ij}^k \geq 0 \quad \text{3h}$$
$$r_j^k \geq 0 \quad \text{3i}$$
$$z_j^k \geq 0 \quad \text{3j}$$
$$\delta_i^-,\ \delta_i^+ \geq 0 \quad \text{3k}$$

7. Stochastic Goal Programming modeling of Supply Chain

After explaining how to incorporate the satisfaction function into GP model in section 4 and formulating the linear and Goal Programming (GP) model of the Supply Chain (SC) in sections 5 and 6, now we are able to formulate the stochastic GP model of supply chain. Our assumption here is that the aspired goals for demand, supply and total cost are random variables with normal probability distribution with mean and standard deviation of $(\mu_d\ ,\ \sigma_d)$, $(\mu_s\ ,\ \sigma_s)$ and $(\mu_c\ ,\ \sigma_c)$, respectively. So the Stochastic Goal Programming (SGP) model of SC can be formulated as:

Program 4-1:

$$\text{Min}\ \{\tilde{\delta}_c^+\ ,\ \delta_n^- + \delta_n^+,\ \tilde{\delta}_d^-,\ \tilde{\delta}_s^+,\ \delta_m^+, \delta_e^+\} \quad \text{4a'}$$

s.t.

$$\sum_{i \in P} c_i y_i + \sum_{k \in K} \sum_{(ij) \in A} q_{ij}^k x_{ij}^k + \sum_{k \in K} \sum_{j \in C} h_j^k z_j^k + \sum_{k \in K} \sum_{j \in C} f_j^k e_j^k + \tilde{\delta}_c^- - \tilde{\delta}_c^+ = \tilde{g}_c \quad \text{4a}$$

$$\sum_{i \in N} x_{ij}^k - \sum_{l \in N} x_{il}^k + \delta_n^- - \delta_n^+ = 0 \qquad \forall j \in P, \quad \forall k \in K \quad \text{4b}$$

$$\sum_{i \in N} x_{ij}^k + z_j^k + \tilde{\delta}_{dj}^- - \tilde{\delta}_{dj}^+ = \tilde{g}_{dj}^k \qquad \forall j \in C, \quad \forall k \in K \quad \text{4c}$$

$$\sum_{j \in N} x_{ij}^k + \tilde{\delta}_{si}^- - \tilde{\delta}_{si}^+ = \tilde{g}_{si}^k \qquad \forall i \in S, \quad \forall k \in K \quad \text{4d}$$

$$\sum_{k \in K} r_j^k (\sum_{i \in N} x_{ij}^k) - \sum_{k \in K} m_j^k y_j^k - \sum_{k \in K} e_j^k + \delta_{mj}^- - \delta_{mj}^+ = 0 \quad \forall j \in P, \quad \forall k \in K, \quad \forall (ij) \in A \quad \text{4f}$$

$$\sum_{k \in K} e_j^k - \sum_{k \in K} y_j^k o_j^k + \delta_{ej}^- - \delta_{ej}^+ = 0 \qquad \forall j \in P, \quad \forall k \in K \quad \text{4h}$$

$$y \in Y \subseteq \{0,1\}^{|P|} \quad \text{4g}$$
$$x_{ij}^k \geq 0 \quad \text{4h}$$
$$r_j^k \geq 0 \quad \text{4i}$$
$$z_j^k \geq 0 \quad \text{4j}$$
$$\delta_i^-,\ \delta_i^+ \geq 0 \quad \text{4k}$$

Then, by application of program 1-2 and replacing the random goals with their means $(\mu_d, \mu_s \text{ and } \mu_c)$ in program 3-2, we can formulate the deterministic equivalent of program 4-1:

Program 5-1:

$$\text{Min}\ \{\delta_c^+,\ \delta_n^- + \delta_n^+,\ \delta_d^-,\ \delta_s^+,\ \delta_m^+, \delta_e^+\} \qquad \text{5a'}$$

s.t.

$$\sum_{i\in P} c_i y_i + \sum_{k\in K}\sum_{(ij)\in A} q_{ij}^k x_{ij}^k + \sum_{k\in K}\sum_{j\in C} h_j^k z_j^k + \sum_{k\in K}\sum_{j\in C} f_j^k e_j^k + \delta_c^- - \delta_c^+ = \mu_c \qquad \text{5a}$$

$$\sum_{i\in N} x_{ij}^k - \sum_{l\in N} x_{il}^k + \delta_n^- - \delta_n^+ = 0 \qquad \forall j \in P, \quad \forall k \in K \qquad \text{5b}$$

$$\sum_{i\in N} x_{ij}^k + z_j^k + \delta_{dj}^- - \delta_{dj}^+ = \mu_{dj}^k \qquad \forall j \in C, \quad \forall k \in K \qquad \text{5c}$$

$$\sum_{j\in N} x_{ij}^k + \delta_{si}^- - \delta_{si}^+ = \mu_{si}^k \qquad \forall i \in S, \quad \forall k \in K \qquad \text{5d}$$

$$\sum_{k\in K} r_j^k (\sum_{i\in N} x_{ij}^k) - \sum_{k\in K} m_j^k y_j^k - \sum_{k\in K} e_j^k + \delta_{mj}^- - \delta_{mj}^+ \ = 0 \quad \forall j \in P, \quad \forall k \in K, \quad \forall (ij) \in A \qquad \text{5f}$$

$$\sum_{k\in K} e_j^k - \sum_{k\in K} y_j^k o_j^k + \delta_{ej}^- - \delta_{ej}^+ = 0 \qquad \forall j \in P, \quad \forall k \in K \qquad \text{5h}$$

$$y \in Y \subseteq \{0,1\}^{|P|} \qquad \text{5g}$$

$$x_{ij}^k \geq 0 \qquad \text{5h}$$

$$r_j^k \geq 0 \qquad \text{5i}$$

$$z_j^k \geq 0 \qquad \text{5j}$$

$$\delta_i^-,\ \delta_i^+ \geq 0 \qquad \text{5k}$$

Now in order to incorporate decision maker's preference, we can apply Program 5-1 and transform the achievement function (5a') into the following statement:

Program 5-2

$$Max \quad \omega_1 F(\delta_c^+) + \omega_2((F(\delta_n^+) + F(\delta_n^-)) + \omega_3 F(\delta_d^-) + \omega_4 F(\delta_s^+) + \omega_5 F(\delta_m^+) + \omega_6 F(\delta_e^+)$$

where $\delta_c = \Sigma\delta_{ci}$, $\delta_s = \Sigma\delta_{si}$ and $\delta_d = \Sigma\delta_{di}$ ($i\in I$) and $F(\delta_c)$, $F(\delta_s)$ and $F(\delta_d)$ denote the DM's satisfaction regarding the deviation of achieved levels from the goals for total cost, supply and demand.

By formulating the achievement function, the last step to SGP modeling of SCM is accomplished. In the next section the program developed in this section is applied to solve a numerical SC problem.

8. Numerical Example:

To explain our model we apply the Supply Chain (SC) network design problem was used by Azaron *et al.* (2010), however the goals in the problem are assumed to be stochastic variables with normal probability distribution in order to fit in our model. According to the problem a wine company wishes to design an AC with three customer centers placed in locations L,M and N , and four suppliers placed in locations A, B, C and D. To build the bottling plants four locations E, F, G and H are considered.

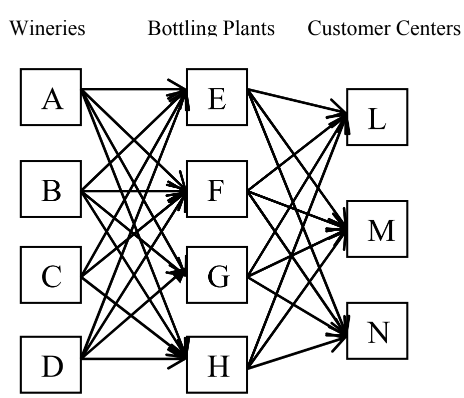

Fig. 2. SC network for numerical example

It is assumed that the shipping capacity, demands at customer centers and total cost (investment costs + transportation costs + production costs + shortage costs) goals are stochastic variables with normal probability distribution:

- The shipping capacity of each winery A, B, C, and D:
  { (μ_{si} , σ_{si}): (375; 15), (187; 17), (250; 10), (150; 20)}
- Demands at customer centers L, M and N:
  {(μ_{dj} , σ_{dj}): (318; 62), (161; 17), (169; 27)}
- Total cost :
  {(μ_c , σ_c): (1,300,000; 10000)}

The value of the other deterministic parameters are listed below

- (475,000, 425,000, 500,000, 450,000) are investment costs for building each bottling plant E, F, G, and H, respectively.
- (65.6, 155.5, 64.3, 175.3, 62, 150.5, 59.1, 175.2, 84, 174.5, 87.5, 208.9, 110.5, 100.5, 109, 97.8) are the unit costs of production and transporting bulk wine from each winery A, B, C, and D to each bottling plant E, F, G, and H, respectively.
- (200.5, 300.5, 699.5, 693, 533, 362, 163.8, 307, 594.8, 625, 613.6, 335.5) are the unit costs of production and transporting bottled wine from each bottling plant E, F, G, and H to each distribution center L, M, and N, respectively.
- (10,000, 13,000, 12,000) are the unit shortage costs at each distribution center L, M, and N, respectively.
- (315, 260, 340, 280) are the capacities of each bottling plant E, F, G, and H, respectively, if it is built.
- (100, 80, 60, 50) are the unit capacity expansion costs at E, F, G and H. We cannot expand the capacity of these plants more than (40, 30, 50, 25) units in any situation.
- The threshold values of the satisfaction function for each goal are:

Objective	$\alpha\mu_i$	σ_i	μ_{total}	σ_{total}	α_{id}	α_{io}	α_{iv}
Total Cost	1,300,000	10,000	1,300,000	10,000	10,000	20,000	30,000
Demand	318,161,169	62,17, 27	648	70	70	140	210
Supply	375, 187,250 ,150	15, 17, 10, 20	962	32	32	64	96
Capacity					40	80	120
Expansion					20	60	60
Flow					40	80	120

Table 1: Figures of the stochastic variable

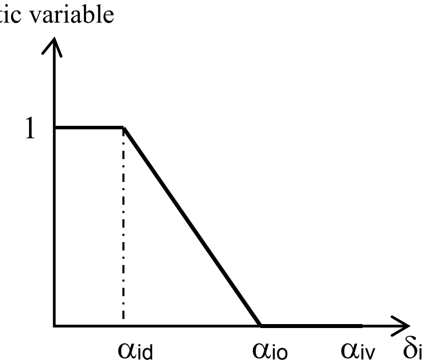

Fig. 3. satisfaction function type applied for the numerical example

After solving the above problem by Lingo software version 11, we reached the following results:

Variable	Value	Variable	Value
DM Satisfaction	1	XEM	0
XAE	205	XEN	226
XAF	0	XFL	0
XAG	140	XFM	0
XAH	0	XFN	0
XBE	0	XGL	189
XBF	0	XGM	161
XBG	0	XGN	0
XBH	0	XHL	0
XCE	0	XHM	0
XCF	0	XHN	0
XCG	250	YE	1
XCH	0	YF	0
XDE	150	YG	1
XDF	0	YH	0
XDG	0	ZL	0
XDH	0	ZM	0
XEL	129	ZN	0

Xij: number of units from winery i to bottling plant j
Xjk: number of units from bottling plant j to customer center k
Rj: Bottling plant capacity expansion
Yj: 1 if bottling plant j is made and 0 otherwise
Zk: unit shortage at customer center k
$i \in \{A,B,C,D\}$, $j \in \{E,F,G,H\}$, $k \in \{L,M,N\}$

Table 2: Results of the numerical example

9. Concluding Remarks

This paper attempts to explicitly incorporate Decision-Maker's preferences in the context of Decision-Making process related to supply chain management where the information is uncertain. We noticed that in the literature the Decision-Maker's preferences are not explicitly introduced in the supply chain management formulations where the decision-making context is uncertain. The proposed Stochastic Goal Programming (SGP) model allows the manger (Decision-Maker) to express his/her experience, tacit knowledge and intuition. In other word, in our model, the manager plays an important role during the decision-making process.

To model the Supply Chain (SC) under uncertainty we applied Chance Constrained Programming (CCP) to transform the objectives from stochastic to deterministic form and then utilized Satisfaction Function concept to explicitly incorporate the Decision Maker's preferences into the model. The aspired level of demand, supply and total cost were assumed to be random variables with normal probability distribution. The model was then applied in a numerical example to decide site location and flow of the product flow in the SC network so that the decision maker's satisfaction is maximized.

Our model can noticeably simplify formulating SC design problems under uncertainty through generating a deterministic equivalent; however it has some limitations that need to be addressed. For example the model assumes that the random goals have normal probability distribution while in real situation the probability distribution may be different. Besides it assumes that only the goals are random while in reality the parameters on the left hand side as well as goal priority may also be stochastic. The other limitation of the model is that it only incorporates cost constraints while Quality and Delivery as well as environmental constraints can also influence the DM's preference. Finally, the model does not address the risk of unwanted deviation of achievement level from the aspired level which is very critical in stochastic environment. While the extensions of this research may involve addressing the above limitations, an interesting research opportunity could be to compare the solutions found by our proposed model with those of the other models in terms of precision versus efforts.

We believe that our formulation can be applied to large scale problems and even for the cases where several Decision-Makers are involved. The satisfaction functions can reflect the preferences of one single Decision-Maker or several stakeholders. In such case, the stakeholders are required to make some compromises in providing one single preference function for each objective. In fact, the next step of our research program is to apply the proposed model to a real decision-making context.

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