An Approach to Evaluate a Supply Chain Network

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***Abstract*— Designing the supply chain network (SCN) is the first step to creating a chain sourcing for results. The process identifies the change that will differentiate an organization from its competitors, to contact a customer with a successful value proposition, reduce costs and boost profitability. The most effective way to ensure perfect fluidity is to appoint an employee responsible for supervising the entire process. The manager will inform and coordinate the activities of the heads of different departments, from shipping to sales, focusing on communication and identification of potential problems, as well as correcting faults before they lead to disruption. This paper proposes an evaluation approach for the supply chain network design problems under uncertainty. Existing approaches to this problem are either the deterministic environments or can only address a modest number of scenarios for the uncertain problem parameters. Our solution approach integrates both features; the collective evaluation and the selection of one.**

***Keywords*—** *Resilience strategies, Supply chain network design, scenario planning, value creation, uncertainty*

1. Introduction

The trading environment nowadays is characterized by two main developments. First, the deep competition in the worldwide economy has affected companies to investigate persistently for expenditure reduction and responsiveness opportunities. Second, supply chain design has become a means of increasing the company's competitive improvement. [23] developed a concept of an economic mechanism for logistics coordination, the interrelated elements of which are: a subsystem for cost management, a subsystem for decision support in operational material flow management, and a subsystem for integrated planning and material flow management. The presented optimization is validated and its effect on real-world production performance is evaluated

This implies that an important utility of the Supply chain design evaluation approach is to characterize the right design. As supply chains are dynamic, different products, services, interdependencies, and processes form different scenarios. A scenario is defined by every possible sequence of environments over a given period. The environment is the internal and external conditions under which the supply chain network operates. It is imperative then to envisage, design, and evaluate different supply chain scenarios before implementing a real one.

Several supply chain scenarios can be described for an organization's supply chain. The coordination structure and performance may vary from one scenario to another. The organization should model the complexities and evaluate the performance of the design generated from a particular scenario before implementing it. An organization requires to understand not only the current scenarios but also how to model and evaluate future designs for the purpose of maintaining competitiveness.

Thus, the contribution of this paper is to develop a new supply chain design evaluation process, which can be used to search for an optimal design. The remainder of this paper is organized as follows: Section 1 presents an overview of the problem; section 2 describes the mathematical formulation of the Supply Chain Network (SCN) design model under uncertainty in literature review. Section 3 elaborates on a supply chain design evaluation methodology based on performance measures and filtering procedures. the complete pathway to an SCN design methodology to advance sustainable value establishment is implemented in section 4, concluded in section 5 and discussed in section 6.

2. Literature review

Having a smooth and efficient supply chain is essential for the strength of a business. Sometimes even the slightest little mistake can be extremely damaging. However, by acquiring the necessary knowledge and dealing with the unexpected, most problems can be avoided. No matter how skilled a business leader is, no company is completely immune to upstream or downstream disruptions in the supply chain.

Regularly reviewing how a supply chain is functioning will provide valuable insight into potential areas for improvement. Setting goals and benchmarking the entire supply chain is the most effective way to keep it running smoothly. The design or redesign of the supply chain network involves many strategic decisions, including the selection of suppliers, choosing transportation means and options, the location and selection of depots, etc. Total cost to serve is frequently used as the most important determinant in the evaluation of supply chain network design, while enough attention in including the importance of the customer's responsibility for the evaluation of the network is easier said than done. Subsequently, the evaluation should be based on response optimization models, where decisions are taken with adaptation to the SCN's environments. This gives rise to the multi-stage decision process through a planning horizon. As the future is unknown and some disturbances may influence the SCN, the best that can be done in anticipation.

Tremendous progress toward an understanding of the properties of stochastic programming models and the design of algorithmic approaches for solving them has been made ([4],[22]). As a result, stochastic programming is achieving recognition as a viable approach for large-scale models of decisions under uncertainty.

[22] addressed in their study uncertainties in building performance evaluations and their potential effect on design decisions. These uncertainties meant that the natural world is buffeted by stochasticity. A specific inventory replenishment policy was applied to the stochastic mathematical model for food waste reduction system and assuming the lifetime of the products to be one day.

However, following [16], the stochastic models are considerably more complicated and possess some inherent randomness. Indeed, the same set of parameter values and initial conditions will lead to an ensemble of different outputs [18].

For the reasons above, we propose a new model that consists of a multi-stage supply chain network where real options can be deployed and exercised periodically, contingent on prevailing scenarios. As a result, the SCN design model under uncertainty is considered a multistage stochastic program with an infinite set of scenarios, a multi-objective reward function, and anticipation of adaptation-response decisions.

It is essential to have a contingency plan in the event of a supply chain failure. It could be, quite simply, to keep the contact details of a rental company in the event of a truck breaking down or a list of temporary workers that can be ready for replacements if some of the employees are absent. Whatever precautions are taken, the time and energy must be devoted to putting in place alternative plans for the entire supply chain network. The links inside an SCN that are most at risk must be identified and a plan for the unexpected is a necessity.

Implement the strategies outlined above, and managers will quickly perceive countless improvements: reduced delivery times, improved customer satisfaction, increased customer loyalty, and increased profits. Therefore, streamlining the supply chain network must be a priority for all businesses.

In this section, we formulate a supply chain network model that can be included in an evaluation ideal.

2.1 Deterministic program

The first step for this formulation begins with the description of a deterministic mathematical formulation for the problem considered.

The main purpose of a company is to manage its product distribution network. This objective is achieved by the simultaneous realization of different factors: an adequate logistics policy, an allocation of production capacity, and a locating distribution center to support these policies. We note that all these decisions are based on the anticipation of the future. To do optimize this specific problem, we recommend using the SCN design.

The objective of an SCN design problem is to maximize discounted expected profits and to take the best decision design for this. Referring to [14], the following notation is used.

$t \in T$: Periods in the planning horizon

$h \in H$: Reengineering cycles in the planning horizon

$t \in T_h$: Periods in the reengineering cycle h

$h(t)$: Reengineering cycle of period t

α : A discount rate, based on the weighted average costs of capital of the company.

X_t : The level of each network's activity in the period $t \in T$

F_t : Flow of the product in period $t \in T$.

I_t : Level of strategic inventory of the product in the period $t \in T$.

U_t : Penalty paid to the vendor under contract if the minimum sales value specified in the contract isn't reached in period $t \in T$.

Y_h : Binary variable equal to 1 if, opening, using, or closing a platform at the beginning of the planning cycle $h \in H$.

W_h : Binary variable equal to 1 if a market policy is selected during cycle $h \in H$.

Z_h : Binary variable equal to 1 if a transportation capacity is selected at the beginning of a cycle $h \in H$.

V_h: Binary variable equal to 1 if a vendor is selected at the beginning of a cycle $h \in H$

A compact deterministic formulation of the supply chain network design problem is presented as follows:

$$Max \sum_{t \in T} \frac{1}{(1+\alpha)^t} [A_t F_t - B_t (F_t, X_t, I_t, U_t, Y_{h(t)}, W_{h(t)}, Z_{h(t)}, Y_{h(t)h(t)})] \quad (1)$$

$s.t$

$$C_t[W_{h(t)}, Y_{h(t)}] \le b_t \ \forall t \in T \quad (2)$$

$$G_t F_t + P_t[W_{h(t)}, Y_{h(t)}, Z_{h(t)}] \le 0 \ \forall t \in T \quad (3)$$

$$M_t[F_t, U_t, X_t, I_t] + O_t[Y_{h(t)}, V_{h(t)}] \le 0 \ \forall t \in T \quad (4)$$

$$L_t[X_t, F_t, I_t] \le d_t \ \forall t \in T \quad (5)$$

$$X_t, F_t, I_t, U_t \ge o \quad \forall t \in T \quad (6)$$

$$Y_{h(t)}, W_{h(t)}, Z_{h(t)}, V_{h(t)} \in \{o,1\} \ \forall t \in T \quad (7)$$

Where (X_t, F_t, I_t, U_t) be the follower variables and $(Y_{h(t)}, W_{h(t)}, Z_{h(t)}, V_{h(t)})$ the design variables or the leader variables. A_t and B_t are two matrices denoting the revenues and expenditures associated to decision variables during the planning horizon. $C_t, G_t, P_t, M_t, O_t, L_t$ are the matrices of parameters. b_t and d_t are two left-side vectors.

Equation (2) presents the constraints related to the market policy and internal location configurations via the use of platform selection variables. Equation (3) presents the goals of the company in demand and penetration level in the market, the reception and shipping capacity limits, and the network transportation capacity restrictions. Equation (4) presents limits of the supplied quantity by the vendor of each product and the benefit of the vendor's contract conditions. In addition to the constraints related to the throughput and inventory level for each platform. Equation (5) is about flow equilibrium constraints, inventory account constraints, and inventory-throughput relationship constraints. Finally, non-negativity and binary constraints are given.

Relative to the resolution of uncertainty, the decision maker must determine when the decisions are made. The previous formulation of the SCN problem does not consider the timing of the decisions. In the following, the recourse program for the SCN problem will be presented.

2.2 Multi-period two-stage stochastic program with recourse

A variety of applications in discrete stochastic multiple criteria decision-making [28], risk into project selection [9], index portfolios [1], etc. can be formulated as two-stage stochastic integer programs. There has been significant development in extensions of the two-stage stochastic integer programming framework, e.g., a novel method based on the stochastic dominance degree [28] and in relation to Separate Utility Models for gains and for losses [27].

In this problem $(\boldsymbol{Y_h}, \boldsymbol{W_h}, \boldsymbol{Z_h}, \boldsymbol{V_h})$ corresponds to the resource levels to be acquired, and ω corresponds to a specific scenario from the whole set of scenarios denoted by Ω.

If the initial decisions are taken in the beginning of the planning horizon, these decisions are denoted by $D_1 = (\boldsymbol{Y_1}, \boldsymbol{W_1}, \boldsymbol{Z_1}, \boldsymbol{V_1})$ describing the first cycle decisions and coupled with a given scenario. In order to model the first order decisions variables as being dependent on the recourse variables, it is necessary to differentiate between the decisions that must be taken at the beginning of the planning horizon in the first cycle (h=1) noted as D_1 and presenting the decisions $(Y_{h(t)}, W_{h(t)}, Z_{h(t)}, V_{h(t)})$ taken in cycle h (h>1) of each period of time t∈T. The former decision variables are defined according to a specific scenario ω∈Ω and they may change from one to another. These design variables are noted by $\left(\boldsymbol{Y}_{h(t)}(D_1, \omega), \boldsymbol{W}_{h(t)}(D_1, \omega), \boldsymbol{Z}_{h(t)}(D_1, \omega), \boldsymbol{V}_{h(t)}(D_1, \omega)\right)$ showing that the design decisions during the cycle periods depend on the first ones taken at the beginning of the planning horizon under a particular scenario. D_1 does not act in response to scenario ω, and it is determined before any information regarding the uncertain data has been obtained.

To take under consideration the structure of this decision problem, we may state the recourse version of the original program as follow:

$$Q(D_1,\omega) = Max \sum_{t\in T} \frac{1}{(1+\alpha)^t} \left[A_t(\omega) F_t(D_1,\omega) \right] - \sum_{h>1} \sum_{t\in T_h} \frac{1}{(1+\alpha)^t} B_{h(t)}(\omega) \begin{bmatrix} F_t(D_1,\omega), X_t(D_1,\omega), I_t(D_1,\omega), U_t(D_1,\omega) \\ , Y_{h(t)}(D_1,\omega), W_{h(t)}(D_1,\omega), Z_{h(t)}(D_1,\omega), V_{h(t)}(D_1,\omega) \end{bmatrix} \quad (11)$$

$s.t$

$$C(\omega)\left[\mathbf{W}_{h(t)}(D_1,\omega), \mathbf{Y}_{h(t)}(D_1,\omega)\right] \le b(\omega) \qquad \forall t \in T \quad (12)$$

$$G(\omega)\mathbf{F}_t(D_1,\omega) + P(\omega)[\mathbf{W}_{h(t)}(D_1,\omega), \mathbf{Y}_{h(t)}(D_1,\omega), \mathbf{Z}_{h(t)}(D_1,\omega)] \le 0 \qquad \forall t \in T \quad (13)$$

$$M(\omega)[\mathbf{F}_t(D_1,\omega), \mathbf{U}_t(D_1,\omega), \mathbf{X}_t(D_1,\omega), \mathbf{I}_t(D_1,\omega)] + O(\omega)[\mathbf{Y}_{h(t)}(D_1,\omega), \mathbf{V}_{h(t)}(D_1,\omega)] \le 0 \quad \forall t \in T \quad (14)$$

$$L(\omega)[\mathbf{X}_t(D_1,\omega), \mathbf{F}_t(D_1,\omega), \mathbf{I}_t(D_1,\omega)] \le d(\omega) \qquad \forall t \in T \quad (15)$$

$$\mathbf{X}_t(D_1,\omega), \mathbf{F}_t(D_1,\omega), \mathbf{I}_t(D_1,\omega), \mathbf{U}_t(D_1,\omega) \ge 0 \qquad \forall t \in T \quad (16)$$

$$\mathbf{Y}_{h(t)}(D_1,\omega), \mathbf{W}_{h(t)}(D_1,\omega), \mathbf{Z}_{h(t)}(D_1,\omega), \mathbf{V}_{h(t)}(D_1,\omega) \in \{0,1\} \qquad \forall t \in T \quad (17)$$

This sub-problem determines the optimal flow, throughput, and inventory level and contract's penalty to perform, after the decisions related to platforms, transportation, policy, and vendor are taken. The decision variables $\left(\mathbf{X}_t(\omega), \mathbf{F}_t(\omega), \mathbf{I}_t(\omega), \mathbf{U}_t(\omega)\right)$ are adapted to the specific combination of $\left(\mathbf{V}_{h(t)}, \mathbf{Y}_{h(t)}, \mathbf{Z}_{h(t)}, \mathbf{W}_{h(t)}\right)$ and ω obtained. If the initial decisions $D_1 = (\mathbf{V}_1, \mathbf{Y}_1, \mathbf{Z}_1, \mathbf{W}_1)$ know as first stage decisions are coupled with a particular outcome, the variables $\left(\mathbf{X}_t(D_1,\omega), \mathbf{F}_t(D_1,\omega), \mathbf{I}_t(D_1,\omega), \mathbf{U}_t(D_1,\omega)\right)$ offer an opportunity to fully recover possible.

The subproblem $Q(D_1,\omega)$ determines the optimal design decisions after the recourse decisions variables are known and it is formulated as follows:

$$Max\sum_{t\in T}\frac{1}{(1+\alpha)^t}\left[A_t(\omega)\mathbf{F}_t(D_1^j,\omega)\right]$$
$$-\sum_{h>1}\sum_{t\in T_h}\frac{1}{(1+\alpha)^t}B_{h(t)}(\omega)\begin{bmatrix}\mathbf{F}_t(D_1^j,\omega),\mathbf{X}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega),\mathbf{U}_t(D_1^j,\omega)\\ ,\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Z}_{h(t)}(D_1^j,\omega),\mathbf{V}_{h(t)}(D_1^j,\omega)\end{bmatrix} \quad (11)$$

$s.t$

$$C(\omega)\left[\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Y}_{h(t)}(D_1^j,\omega)\right]\le b(\omega) \qquad \forall t\in T \quad (12)$$

$$G(\omega)\mathbf{F}_t(D_1^j,\omega)+P(\omega)[\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{Z}_{h(t)}(D_1^j,\omega)]\le 0 \qquad \forall t\in T \quad (13)$$

$$M(\omega)[\mathbf{F}_t(D_1^j,\omega),\mathbf{U}_t(D_1^j,\omega),\mathbf{X}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega)]+O(\omega)[\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{V}_{h(t)}(D_1^j,\omega)]\le 0 \quad \forall t\in T \quad (14)$$

$$L(\omega)[\mathbf{X}_t(D_1^j,\omega),\mathbf{F}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega)]\le d(\omega) \qquad \forall t\in T \quad (15)$$

$$\mathbf{X}_t(D_1^j,\omega),\mathbf{F}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega),\mathbf{U}_t(D_1^j,\omega)\ge 0 \qquad \forall t\in T \quad (16)$$

$$\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Z}_{h(t)}(D_1^j,\omega),\mathbf{V}_{h(t)}(D_1^j,\omega)\in\{0,1\} \qquad \forall t\in T \quad (17)$$

It is necessary to specify that the matrixes of parameters and costs on both sides of the sub-problems depend also on the scenarios and may change from one scenario to another.

The resulting stochastic program (8)-(17) is resolved for every generated scenario $\omega\in\Omega$.

The comparison and the selection of solutions (designs) are performed by means of several performance measures defined next sections.

3. Design evaluation approach

This section describes an evaluation approach to multi-objective design optimization that helps to identify optimum designs with uncertainty during the complete planning horizon. The objective of the design evaluation level is to choose the best SCN design among those considered including the status quo. The finite set of designs is denoted by J where J≥2.

During the planning period, anticipation is made in order to give the users or the designers the opportunity to respond to future business environment disruptions and to adjust the structure of the SCN. Therefore, the design evaluation procedure should be based on a response optimization model formulated as follow:

$$Max\sum_{t\in T}\frac{1}{(1+\alpha)^t}\left[A_t(\omega)\mathbf{F}_t(D_1^j,\omega)\right]$$
$$-\sum_{h>1}\sum_{t\in T_h}\frac{1}{(1+\alpha)^t}B_{h(t)}(\omega)\begin{bmatrix}\mathbf{F}_t(D_1^j,\omega),\mathbf{X}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega),\mathbf{U}_t(D_1^j,\omega)\\ ,\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Z}_{h(t)}(D_1^j,\omega),\mathbf{V}_{h(t)}(D_1^j,\omega)\end{bmatrix} \quad (18)$$

$s.t$

$$C(\omega)\left[\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Y}_{h(t)}(D_1^j,\omega)\right]\le b(\omega) \qquad \forall t\in T \quad (19)$$

$$G(\omega)\mathbf{F}_t(D_1^j,\omega)+P(\omega)[\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{Z}_{h(t)}(D_1^j,\omega)]\le 0 \qquad \forall t\in T \quad (20)$$

$$M(\omega)[\mathbf{F}_t(D_1^j,\omega),\mathbf{U}_t(D_1^j,\omega),\mathbf{X}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega)]+O(\omega)[\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{V}_{h(t)}(D_1^j,\omega)]\le 0 \quad \forall t\in T \quad (21)$$

$$L(\omega)[\mathbf{X}_t(D_1^j,\omega),\mathbf{F}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega)]\le d(\omega) \qquad \forall t\in T \quad (22)$$

$$\mathbf{X}_t(D_1^j,\omega),\mathbf{F}_t(D_1^j,\omega),\mathbf{I}_t(D_1^j,\omega),\mathbf{U}_t(D_1^j,\omega)\ge 0 \qquad \forall t\in T \quad (23)$$

$$\mathbf{Y}_{h(t)}(D_1^j,\omega),\mathbf{W}_{h(t)}(D_1^j,\omega),\mathbf{Z}_{h(t)}(D_1^j,\omega),\mathbf{V}_{h(t)}(D_1^j,\omega)\in\{0,1\} \qquad \forall t\in T \quad (24)$$

3.1 Performance measures

In practice, there are two expense types which are constrained by different expenditure control mechanisms. Firstly, the costs of operating depots to stock inventories, the investments costs, the maintenance costs required to control transportation of products. Secondly, the operative costs related to the supply, and recourse actions taken during the planning horizon. The extensive literature on the performance measures of SCNs comprises the study suggested by [14], which proposes a generic design methodology that was used to obtain effective and robust SCNs. [24] have solved the spot market behavior by using a sample average approximation method based on Monte Carlo sampling techniques.

Many methods are used to generate scenarios and the most used one is the Monte Carlo method as presented in [14] and [17].

[2] present a practical convex hull algorithm that associates the two-dimensional Quickhull algorithm with the general-dimension Beneath-Beyond Algorithm. The persistence of this algorithm is proved because it runs faster when the input does not contain extreme points and it is provided empirical evidence that the algorithm runs faster when the input contains no-extreme points and it used less memory.

However, the problem is difficult to solve due to the infinite number of probable future scenarios. To overcome this problem, some reductions on its complexity are needed. This is done by the way that the set of generated scenarios Ω^P is replaced by representative equiprobable scenarios with probability $\frac{1}{M}$ where M is the number of independent small Monte Carlo samples.

Several plausible future scenarios are generated in independent samples of M_A acceptable-risk scenarios and M_S serious risk scenarios and M_U worst-case scenarios used in the filtering procedure. All these samples are generated with their respectively estimated probabilities π_A, π_S, π_U.

To illustrate the various sources of uncertainty, the set of scenarios is portioned into two mutually exclusive and collectively exhaustive subsets [3]; Ω^P for probabilistic scenarios without deeply uncertain events and Ω^U for others. A given scenario is defined into a set Ω^P; where $P = \{A, S\}$ and the recourses decisions $(\mathbf{X}_t, \mathbf{F}_t, \mathbf{I}_t, \mathbf{U}_t)$ adapt to the specific combination of $(\mathbf{Y}_h, \mathbf{W}_h, \mathbf{Z}_h, \mathbf{V}_h)$ and ω obtained. The set $\Omega^M = \Omega^{M_A} + \Omega^{M_S}$ is used in the evaluation stage of designs apart from the worst-case scenarios Ω^U related to deep uncertainty scenarios that will be used as a decisive factor in the filtering procedure; in the way that the designs performing well in worst-case scenarios will be selected.

To evaluate the entire set of designs, a set of performance measures $M_i = \{M_1, M_2, ..., M_m\}$, $(m \geq 2)$ is needed.

Let $\forall t \in T, \omega \in \Omega^M$

$$NOP_t(D_1^j, \omega) = \left[A_t(\omega)\mathbf{F}_t(D_1^j, \omega)\right] - B_{h(t)}(\omega)\begin{bmatrix}\mathbf{F}_t(D_1^j, \omega) + \mathbf{X}_t(D_1^j, \omega) + \mathbf{I}_t(D_1^j, \omega) + \mathbf{U}_t(D_1^j, \omega) \\ +\mathbf{Y}_{h(t)}(D_1^j, \omega) + \mathbf{W}_{h(t)}(D_1^j, \omega) + \mathbf{Z}_{h(t)}(D_1^j, \omega) + \mathbf{V}_{h(t)}(D_1^j, \omega)\end{bmatrix} \quad (18)$$

$NOP_t(D_1^j, \omega)$ presents the net operating profits of design D_1^j in every period t.

And let

$$NOP(D_1^j, \omega) = \sum_{t \in T} \frac{1}{(1+\alpha)^t} NOP_t(D_1^j, \omega) \quad , \forall t \in T, \omega \in \Omega^M \quad (19)$$

be the discounted net operating profits of a design D_1^j over the planning horizon T.

In this framework, we consider that the key performance indicators are the gain (design value) and the resilience of the design. These indicators are described as follows.

3.2.1. Design value

In this context, the net operating profits over the planning horizon is used to determine the value added by the SCN under a scenario $\omega \in \Omega^M$.

Where

$$NOP(D_1^j,\omega)=\sum_{t\in T}\frac{1}{(1+\alpha)^t}NOP_t(D_1^j,\omega) \quad ,\forall t\in T,\omega\in\Omega^M \quad (20)$$

In the case where the designs are generated by the Monte Carlo approach the estimated probabilities are $\frac{1}{M_A}$ and $\frac{1}{M_S}$ for acceptable and serious scenarios respectively.

The first performance measure deducted from the design value indicator is its expected return value expressed as follows:

$$E\left[NOP(D_1^j)\right]=\sum_{P=A,S}\frac{\pi_P}{M_P}\sum_{\omega\in\Omega^{M_P}}NOP(D_1^j,\omega) \quad (M1)$$

And to ensure the robustness of a design during the planning horizon, the second performance measure can be its mean semi-deviation formulated as:

$$MSD\left[NOP(D_1^j)\right]=\sum_{P=A,S}\frac{\pi_P}{M_P}MSD_P\left[NOP(D_1^j)\right] \quad (M2)$$

In this evaluation approach we use the expected return value under the deep uncertain scenarios as a critical measure formulated by the minimum return value of the design under this type of scenario.

$$DEV\left[NOP(D_1^j)\right]=\min_{\omega\in\Omega^{M_U}}\left\{NOP(D_1^j,\omega)\right\} \quad (M3)$$

3.2.2. Resilience

Due to business disruptions during the planning horizon the SCN operations can be perturbed. The proposed stochastic programming anticipates response policies through decisions variables $\left(\mathbf{X}_t(D_1,\omega),\mathbf{F}_t(D_1,\omega),\mathbf{I}_t(D_1,\omega),\mathbf{U}_t(D_1,\omega)\right)$. The costs associated to these variables must be minimized by providing better resilience strategy. We define the resilience of a generated design as the minimum distance between every demand zone location in the SCN and the second warehouse location which is considered as an alternative in the case of damage in the first warehouse.

This performance indicator is formulated as follows:

$$RES(D_1^j)=\sum_{P=A,S}RES_P(D_1^j)+RES_U(D_1^j)$$

The performance measure extracted from this indicator can be the mean of all the resilience values of the design under every scenario. The selected design will be the one that has the minimum mean value.

$$\overline{RES}(D_1^j)=\sum_{P=A,S}\pi_P\overline{RES_P}(D_1^j)+\pi_U\overline{RES_U}(D_1^j) \quad (M4)$$

3.2 Filtering procedure

The decision-maker is not always a single individual. In fact, much of decision theory has evolved as the result of the need to evaluate decisions faced by groups of individuals or organizations. If the performances among different consequences are similar for al individuals in a group or organization, the group can be viewed as a single decision-making entity. If, on the other hand, the preferences of group members are disparate, the decision analysis becomes more complicated.

[15] indicated that we accept the existence of different types of non-determinism if we are dealing with non-deterministic situations in multi-attribute context.

In this problem, we assume that we have only one decision-maker and not a group of decision makers.

To filter the designs among all the generated ones there are many decision-making techniques, a new technique presented in [12]. The objective of this method proposed by [12] is to determine a set of designs formed by adding mutually efficient subsets of designs called kernels that are obtained through a stepwise procedure, the set of these kernels is denoted by ***K***. The subset ***K*** selected at each step is globally efficient compared to designs not yet selected and relatively homogenous in that comparison. The scenario-based approach allows the decision maker to think deterministically about the problem by attaching causal links to a small number of potential outcomes, instead of using probability distributions [8]. Using a scenario approach has distinct practical advantages, but also presents the inherent danger that meaningful information is ignored ([8], [19]).

The idea in this paper is that an outranking relationship is used to eliminate some generated designs $X^j \quad j=0,1,\dots,J$. This outranking relationship is defined by a level of concordance denoted by θ and a level of disagreement denoted by φ providing the value of each performance measure. As a result, only when the highest level of concordance and the lowest level are guaranteed that some designs will be excluded.

The ranking process needed to give probabilities of selection as in [10] is modified to consider the uncertainties present in the system being optimized. This technique is shown to be effective in reducing the disturbances to the evolutionary algorithm caused by noise in the objective function and provides a simple mathematical basis for describing the ranking and selection process of multi-objective and uncertain data.

To more explain the idea, suppose that a design D_1^j dominates another design D_1^k in all the set of performance measures. In this case, the two levels of concordance θ and disagreement φ that D_1^j dominates D_1^k is a perfect score. The difficulty that is such case is very rare. For this, required levels of concordance and disagreement must be attained to conclude that a design dominates another one.

3.2.1. Required level of concordance

This research area is associated to assessing, selecting, and evaluating options from the best to the worst regarding conflict criteria using experts' preferences [5].

The scenario-based approach permits the decision maker to think deterministically about the problem by attaching causal links to a small number of potential outcomes, instead of using probability distributions [8].

Let $\phi_i^P(D_1^j, D_1^k)$ be a binary variable gives the dominance relationship between every pair of designs based on the set performances measures $M_i = \{ M_1, \ldots, M_m \}$ under scenarios Ω^P, $P = A, S$.

$$\phi_i^P(D_1^j, D_1^k) = \begin{cases} 1 & if \;\; M_i[D_1^j, \Omega^P] \geq M_i[D_1^k, \Omega^P] \\ 0 & otherwise \end{cases} \qquad j,k \in J,\; j \neq k, \quad i = 1,\ldots,m, \quad P = A,S$$

Where $M_i[D_1^j, \Omega^P]$ and $M_i[D_1^k, \Omega^P]$ are respectively the performance measures values of both designs $j,k \in J$ under scenario Ω^P, $P = A, S$ .Let

$$C(D_1^j, D_1^k) = \sum_{P=A,S} \frac{1}{m} \sum_{i=1}^{m} \phi_i^P(D_1^j, D_1^k), \quad \forall j,k \in J,\; j \neq k$$

$C(D_1^j, D_1^k)$ gives us comparisons between designs under both types of scenarios $\Omega^P, P = A, S$.

Based on two levels of concordance θ^A, θ^S of acceptable and serious scenarios respectively, a design D_1^j dominates D_1^k if $C\left(D_1^j, D_1^k\right) \geq (\theta^A \times \theta^S)$. Let $\theta = (\theta^A \times \theta^S)$ be the level of concordance.

3.2.2. Required level of disagreement

Referring to [12], [6], and based on the ELECTRE method; this level ensure that the design selected must guarantee that its minimum value in every performance level do not be less than a given level φ .

Let $\psi_i^P(D_1^j, D_1^k)$ be a binary variable gives the dominance relationship between every pair of designs based on the set performances measures $M_i = \{ M_1, \ldots, M_m \}$ under scenarios $\Omega^P, P = A, S$.

$$\forall\, j,k \in J,\; j \neq k, \quad i = 1,\ldots,m, P = A,S$$

$$\psi_i^P(D_1^j, D_1^k) = \begin{cases} 1 & if \;\; Min\left(M_i[D_1^j, \Omega^P]\right) \geq Min\left(M_i[D_1^k, \Omega^P]\right) \\ 0 & otherwise \end{cases}$$

Let

$$U(D_1^j, D_1^k) = \underset{i}{Max}\left(\psi_i^A(D_1^j, D_1^k), \psi_i^S(D_1^j, D_1^k)\right) \quad \forall j,k \in J,\; j \neq k$$

Based on this, a design D_1^j dominates D_1^k if $U\left(D_1^j, D_1^k\right) \geq \varphi$.

Subsequently to these levels, the set of kernels of selected designs will be a result from a compromise between all the performance measures under different scenarios. This compromise is based on three properties:

- External consistency: any design that is not included in the subset ***K*** must be outranked by at least one of designs of ***K***. This property means that being outranked for a design is not a cause of elimination if the outranking does not originate from a selected design.

- Internal consistency: the set ***K*** does not include any design that is outranked by another one in ***K*** itself. This propriety is needed to mitigate possible resentment between the performance measure values.

Consequently, proprieties 1, 2 are mathematically formulated to get the highest degrees of required concordance level and the required disagreement level φ .

Let $\gamma(D_1^j, D_1^k)$ be the required level of concordance where

$$\gamma(D_1^j, D_1^k) = \begin{cases} 1 & if \;\; C(D_1^j, D_1^k) \geq \theta \\ 0 & otherwise \end{cases}$$

Let $\eta(D_1^j, D_1^k)$ be the required level of disagreement where

$$\eta(D_1^j, D_1^k) = \begin{cases} 1 & if \;\; U(D_1^j, D_1^k) \geq \varphi \\ 0 & otherwise \end{cases}$$

Then a design D_1^j dominates another design D_1^k at the concordance level of $\theta = (\theta^A \times \theta^S)$ if $\gamma(D_1^j, D_1^k) = 1$ and of the disagreement level of φ.

The outranking relationships between the designs can be expressed equivalently as follows:

$$\theta + \gamma(D_1^j, D_1^k) \leq C(D_1^j, D_1^k) + 1 \quad \forall j,k \;\; j \neq k$$
$$\varphi + \eta(D_1^j, D_1^k) \leq U(D_1^j, D_1^k) + 1 \quad \forall j,k \;\; j \neq k$$

Based on [20], the internal and external consistencies require that the set ***K*** must satisfy the following conditions simultaneously:

$$\sum_{k \neq j} \gamma(D_1^k, D_1^j) \times \beta(D_1^k) + \beta(D_1^j) \geq 1 \qquad \forall j$$
$$\sum_{k \neq j} \eta(D_1^k, D_1^j) \times \beta(D_1^k) + \beta(D_1^j) \geq 1 \qquad \forall j$$
$$\sum_{k \neq j} \gamma(D_1^k, D_1^j) \times \beta(D_1^k) + (n-1)\beta(D_1^j) \leq n-1, \quad \forall j$$
$$\sum_{k \neq j} \eta(D_1^k, D_1^j) \times \beta(D_1^k) + (n-1)\beta(D_1^j) \leq n-1, \quad \forall j$$

Where $\beta(D_1^k) = \begin{cases} 1 & if \quad D_1^k \in \mathrm{K} \\ 0 & otherwise \end{cases}$

Finally, the entire program to find the highest level of concordance can be expressed as follows:

$$\begin{aligned}
& Max\,(\theta + \varphi) \\
& s.t \\
& \theta + \gamma(D_1^j, D_1^k) \leq C(D_1^j, D_1^k) + 1 && \forall j,k \;\; j \neq k \\
& \varphi + \eta(D_1^j, D_1^k) \leq U(D_1^j, D_1^k) + 1 && \forall j,k \;\; j \neq k \\
& \sum_{k \neq j} \gamma(D_1^k, D_1^j) \times \beta(D_1^k) + \beta(D_1^j) \geq 1 && \forall j \\
& \sum_{k \neq j} \eta(D_1^k, D_1^j) \times \beta(D_1^k) + \beta(D_1^j) \geq 1 && \forall j \\
& \sum_{k \neq j} \gamma(D_1^k, D_1^j) \times \beta(D_1^k) + (n-1)\beta(D_1^j) \leq n-1, && \forall j \\
& \sum_{k \neq j} \eta(D_1^k, D_1^j) \times \beta(D_1^k) + (n-1)\beta(D_1^j) \leq n-1, && \forall j \\
& M_i[D_1^j, \Omega^U] \times \beta(D_1^j) \geq W_i && \forall i = 1,\dots,m \;\; \forall j \\
& \gamma(D_1^k, D_1^j),\; \eta(D_1^k, D_1^j),\; \beta(D_1^j) \in \{0,1\} && \forall k, j \\
& \theta, \varphi \in \{0,1\}
\end{aligned}$$

Where $P_i\,[D_1^j, \Omega^U]$, is the value of design D_1^j under worst case scenarios Ω^U and $\boldsymbol{W_i}$ is the acceptable level of this value. In other way, a design will be selected as if its performance measures values in deep uncertainty scenarios are bigger than a level $\boldsymbol{W_i}$ fixed by the decision maker for every performance measure.

4. Implementation

Numerical example is designed and implemented to support a simulation prototype with hypotheses of the approach. A set of criteria used in evaluating D_1^j designs is presented in Table1:

Table 1. the set of criteria used in evaluating designs

Criteria	Justification
Direct economic impact	Improved quality and productivity
Indirect economic impact	Better quality and lesser prices
Technological impact	Adoption of new technology
Scientific impact	Use of scientific knowledge
Social impact	Respecting to defined objectives
Resource requirements	Transformed in monetary units
Probability of success	The use of higher living standards

Assignment of scores to D_1^j designs are given on a scale of 0-100 points with respect to the criterion ***r***.

let S_{jr} be the score of the design D_1^j according to criterion ***r*** presented in Table 2 as follow:

Table 2. scores S_{jr} given for seven D_1^j designs

D_1^j designs	indirect economic S_{j1}	direct economic S_{j2}	Technological impact S_{j3}	Social impact S_{j4}	scientific impact S_{j5}	Resource requirements S_{j6}
D_1^1	67,56	70.64	64.57	44.74	47,82	86.30
D_1^2	58.96	64.67	57.48	42.67	46.85	91.10
D_1^3	23.42	19.82	7.21	10.29	5.89	49.32
D_1^4	46.96	49.01	25.11	19.83	18.99	65.87
D_1^5	47.96	47,83	32.84	31.23	28.37	72.94
D_1^6	57.88	77.12	34,83	28,71	26.19	87.97
D_1^7	49.84	54.21	38.59	31.59	19.11	84.15

For implementation use, we developed an algorithm to apply the evaluation and selection methodology. To achieve explanations from the selection model, using experimental instances, requires some supplementary effort. The selection model includes constraints having nonlinear statements and consequently requires to be linearized. The method of [20], for instance, can be used for this use. As in the case of the evaluation models, the computational constraint of the selection models was contained by acceptable limits. for each measure of the selection model involved nearly 200 simplex iterations, and 30 branch and bound nodes. The mathematical model presented in this paper is coded on GAMS 24.1.3 and run by CPLEX 12.5.1.0 solver on an Intel (R) Core (TM) i7-3770 Dual Processor with 16GB RAM and a 2.80GHz CPU. The calculations were made on IBM using MPSX system. From literature review, it is assumed that GAMS-CPLEX can solve the large-scale model having significant number of scenarios, variables, and equations with reasonable computation time.

The idea is to find a Kernel $\mathcal{K}_t$ from the set of the designs remaining R_t subject to the availability of funds (β_t) at step t. with time, D_1^j program ($\mathcal{P}$) is obtained by adding the kernels which are identified regarding step t.

We propose that the acceptable level W_i =30. In other way, a design will be selected if its performance measures values are bigger than a level 30.

The transition from a step to another is done by the following statements

$$\mathcal{P}_t = \mathcal{P}_{t-1} + \mathcal{K}_t$$

$$F_t = F_{t-1} + b_t$$

$$R_t = R - \mathcal{P}_{t-1}$$

$$\beta_t = \beta - F_{t-1}$$

$$t := t+1$$

where:

R: is the initial set of D_1^j designs.

ß: is the sum of the available funds allocated to **R**

F_t: is the amount of funds used regarding step t

b_t: is the budget needed for the D_1^j designs included in kernel $\mathcal{K}_t$.

we suppose that the sum of available funds is β = 1,000.00$

Actions of the algorithm:

Step1: $\mathcal{P}_0 = \emptyset$, $t=0$, $F_0 = 0$

Step2 : $t=t+1$, $R_t = R - \mathcal{P}_{t-1}$, $\beta_t = \beta - F_{t-1}$

Step3: if $R_t = \emptyset$ and $b_t < W_i$, $\forall i = 1,\ldots,m$ then go to ***step 4***, if not then stop and $\mathcal{P}_t = \mathcal{P}_{t-1}$

Step 4: use the evaluation models to compute $M_i[D_1^j, \Omega^U]$ and $M_i[D_1^j, \Omega^P]$

Step 5: use the selection model for R_t with $\beta_t = \beta$

Step 6: find the kernel $\mathcal{K}_t$.

Step 7: $\mathcal{P}_t = \mathcal{P}_{t-1} + \mathcal{K}_t$ and $F_t = F_{t-1} + b_t$

Step 8: repeat ***Step2***

Table 3. Results

t	Ƥ$_t$	Ҡ$_t$	Ɽ$_t$	Ƒ$_t$	ß$_t$	b$_t$	$\theta=(\theta^{A}\times\theta^{S})$	CPU time (seconds)
1	$\{D_1^3\}$	$\{D_1^3\}$	Ɽ	0.00	1,000,00	46.00	1.00	1.935
2	Ƥ$_1$+ $\{D_1^7\}$	$\{D_1^7\}$	Ɽ- Ƥ$_1$	39	964.00	44.60	1.00	3.135
3	Ƥ$_2$+ $\{D_1^2\}$	$\{D_1^2\}$	Ɽ- Ƥ$_2$	80.60	919.40	34.10	1.00	5.195
4	Ƥ$_3$+ $\{D_1^1\}$	$\{D_1^1\}$	Ɽ- Ƥ$_3$	144.70	855.30	28.00	1.00	10.545
5	Ƥ$_4$+ $\{D_1^4\}$	$\{D_1^4\}$	Ɽ- Ƥ$_4$	172.70	727.30	32.10	1.00	20.577
6	Ƥ$_5$+ $\{D_1^1, D_1^5, D_1^3, D_1^2\}$	$\{D_1^1, D_1^5, D_1^3, D_1^2\}$	Ɽ- Ƥ$_5$	204.80	695.20	215.58	1.00	30.873
7	Ƥ$_6$+ $\{D_1^1\}$	$\{D_1^1\}$	Ɽ- Ƥ$_6$	505.50	494.50	35.40	1.00	41.138
8	Ƥ$_7$+ $\{D_1^3, D_1^1, D_1^2, D_1^7\}$	$\{D_1^3, D_1^1, D_1^2, D_1^7\}$	Ɽ- Ƥ$_7$	540.90	459.10	351.80	1.00	57.018
9	Ƥ$_8$+ $\{D_1^2, D_1^5\}$	$\{D_1^2, D_1^5\}$	Ɽ- Ƥ$_8$	892.70	107.30	72.00	0.00	74.803
10	Ƥ$_9$	_	Ɽ- Ƥ$_9$	934.74	35.30	0.00	_	101.120

As can be seen from results in table 3, step 1 of the algorithm suggests design number 3, D_1^3 since ***Ҡ$_1$*** = $\{D_1^3\}$. The budget required by ***Ҡ$_1$*** is b_t=46.00$.

The four next steps suggest the choice of only one design at a time. Step 2 , 3,4 and 5. However, step 6 gives a set of multiple designs to be selected. Four designs for step 6, with a total budget needed equal to 215.58$ wich is lesser than the available budget ***ß$_6$*** =695.20$.

Four selected designs for step 8 with 351.80$ need as a budget, and two selected designs in step 9 which are D_1^2 and D_1^5 with a budget of 72.00$.

step 10 is exceptional because no design is selected since no kernel can be found without exceeding the available budget ***ß$_5$*** =934.74$.

obviously, the insertion of any design remaining outside violates the budgetary constraint of the selection model. Therefore the D_1^j program obtained at the end is Ƥ = {1,2,3,5,7}. We remark that the sixth design D_1^6 is not selected at all.

5. Conclusion

The literature on SCN design problems is wide-ranging. Yet, some features of the problem are overlooked. Most design models make substantial hypothesis and explanations decreasing tiny of current professional requirements.

Altogether, these features mark the elaboration

of SCN design models taking the principle of real problems relatively multifaceted. In this paper, we identify that the formulated SCN model must raid an equilibrium between practicality and manageability, by means of data available in classic real-world frameworks. Reaching this objective remains a significant experiment.
The strategic review of a SCN will result in a series of plans for the organization into the future. With these plans, the business strategy and the tactical and operational implementation of the optimization plans will be covered.

6. Discussion

The main research directions in this paper suggest improving a full approach for SCN design under uncertainty like SCN risk analysis, modelling resilience and responsiveness, SCN hazards modelling, solution methods, scenario development and sampling.

In this estimation, though, the research guidelines suggested in this paper offer a pathway to a SCN design methodology advance sustainable value establishment.

The results obtained from a simulation model indicates the nature of benefits that are proceeding between elements. But the presented outranking scheme is sufficient to ensure that any design will not be chosen before design if design outranks design.

In summary, the suggested methodology may well be useful in supporting a structure for settling a compromise of choice.

Finally, the establishment of this framework could be accompanied by other real implementation of this program or to use a simulation technique and an evaluation framework which will closely monitor progress realized. After all, the results could provide policymakers with new tools to develop new strategy.

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