Dealing with Variations for a Supplier Selection Problem in a Flexible Supply Chain

A Dynamic Optimization Approach

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Abstract: Supply chains are complicated dynamical systems due to many factors, e.g. the competition between companies, the globalization, demand fluctuations, sales forecasting. Hence, they must react to changes in order to adapt quickly its network. In this paper we focus on a two echelon supply chain problem dealing with supplier selection issue during periods in a highly flexible context. How to select suppliers is the main question we try to answer in this research. A suggested approach based on dynamic optimization is highlighted to solve this problem.

1 INTRODUCTION

Dynamic considerations have led researchers to find suitable models for the supply chain system. Various factors characterize the changing environment e.g. arrival of new tasks, suppliers unable to meet demand increases, delivery breakdowns, customer demand forecasts. For these reasons supply chains must adapt their networks to cope with these new situations over time. Notions such as Flexibility and adaptation have emerged in the literature to deal with changes that may affect the supply chain. In this context, *Flexibility* presents a primordial key to cope with perturbations that may affect structures of networks. Thus, supply chains must have ability to synchronize their networks during the changes. *Adaptability* is expressed to deal with problems that may affect the supply chain. (Lee, 2004) describes adaptability as the ability to adjust the supply chain's design to meet structural shifts in markets and modify the supply network to reflect changes in strategies, technologies and products.

Supplier selection problem is one of numerous problems dealing with the structure of the supply chain. Supplier's capacity, lead time and various cost parameters are subject to change over time. Hence the optimal set of supplier can change from a period to another. In the literature this kind of problems is known as *Dynamic Supplier Selection Problem*. A great number of conceptual and empirical works have been published dealing with this problem. However, this selection must be part of a dynamic approach that will help to implement the appropriate network. Indeed, how to adapt supply chain is extremely difficult to determine in a dynamic market that is constantly moving and where prices fluctuate over time.

Recently dynamic optimization have been used to cope with issues that operate in a similar environment in many sectors. To our knowledge, researches based on dynamic optimization have been rarely used in a supply chain context.

This paper seeks to contribute to the configuration of a two echelon supply chain based on a supplier selection issue in a flexible context by proposing an approach based on dynamic optimization that will allows to find the suitable set of suppliers in response to changes to cope with variations in costs in a changing environment depending on market developments and sensitivity.

The rest of this paper is structured as follows. Section 2 reviews the existent literature on adaptable and reconfigurable supply chain issues putting a focus on supplier selection works. Section 3 describes the main features of the problem considered. Main contribu-

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tions of the dynamic optimization approach are discussed in section 4. We conclude the paper by summarizing the most important features of the method adopted and recommend research directions.

2 RELATED RESEARCH

Several papers have focused on the structure of the supply chain treating numerous problems. Issues such as the selection of suppliers and inventory management (Kristianto et al., 2012) were addressed to meet the needs of reconfiguration in the supply chain. (Oh et al., 2011) highlight a method of reconfiguring the supply network of an enterprise to cope with flexible strategies, to illustrate the influence in a dynamic global market environment on the structure of the supply chain. They treat in their paper two types of strategies, flexible procurement and flexible manufacturing in order to evaluate the supply network flexibility in terms of numerical comparison based on an indicator called "suitability of the reconfiguration of supply network". In their article, (Osman and Demirli, 2010) propose a bilinear goal programming model solved by a modified Benders decomposition algorithm for supply chain reconfiguration and supplier selection in response to the increased demand and customer satisfaction requirements regarding delivery dates and amounts. Other researchers have adopted a multi-agent technology to facilitate the flexibility to handle reconfiguration issues (Ryu and Jung, 2003).

Among these different works dealing with the change in the supply chain structure, the supplier selection problem appear like one of the most common issue in term of change in the network. In the literature this problem is modeled in two ways: quantitative models and qualitative models. In order to select the best supplier, tangible and intangible criteria are highlighted through papers. (Ghodsypour and O'Brien, 1998) present a decision support system using an integrated analytic hierarchy process (AHP) and linear programming. (Nazari-Shirkouhi et al., 2013) presented a Supplier selection and order allocation problem using a two-phase fuzzy multi-objective linear programming. (Wu et al., 2009) used an integrated multi-objective decision-making process for supplier selection with bundling problem. Analytic network process (ANP) and mixed integer programming (MIP) are provided to optimize the selection of supplier. (Deng et al., 2014) solved a supplier selection problem using (AHP) methodology extended by effective and feasible representation of uncertain information denoted D-numbers. A (D-AHP) method is proposed for the supplier selection problem, which extends the classical analytic hierarchy process method. (Ding et al., 2005) used an optimization via simulation approach using genetic algorithm for supplier selection issue. Discrete-event simulation is used for performance evaluation of a supplier portfolio and the genetic algorithm is proposed for optimum portfolio identification based on performance index estimated by the simulation.

Following the adequate set of suppliers for all periods of supply due to variation of information (e.g. to quantity shipped at each period, lead time, costs.) seems interesting. Indeed, suppliers for one period may not be the best ones for another period. To our knowledge only one paper focuses on multi period for supplier selection problem. (Ware et al., 2014) developed a mixed-integer non linear program to cope with dynamic supplier selection problem during periods. This paper is based on a static optimization and it doesn't cope with the dynamic market of supply chain. They do not take into account, for example, variation of parameters during a period.

As a result, providing a dynamic approach in order to cope with the dynamic aspect of this issue over time seems interesting. In this paper we propose such a dynamic approach dealing with cost variation during period based on dynamic optimization in order to select the right set of suppliers after each change.

3 PROBLEM FORMULATION

For sake of clarity we decide in this paper to rely on a simple problem of a two-echelon supply chain. We assume that there are two major types of actors: a single customer who wants to be delivered a quantity of one type of product by a set of suppliers. The production capacity of all suppliers allows the delivery of products to the customer.

The notation used of the problem are presented as follows:

- Δ : Set of sub-period. $\delta \in \Delta : \{1, 2, ...n\delta\}$
- S : Set of suppliers. $s \in S : \{1, 2, ...ns\}$
- k_s^δ : Maximal capacity of a supplier s at sub-period δ
- D : Demand of product for a customer
- Cu_s^δ: Unit cost of one product at supplier s at sub-period δ
- Ca_s^δ: Assignment cost for a supplier s at sub-period δ

The customer can order a quantity of products to a number of suppliers for a supply in the beginning of a period. However, throughout this period, changes may occur. Unit cost and assignment cost of suppliers are subject to change over time. Hence, the command issued at the beginning of a period does not necessarily cope with the most appropriate network to deliver the quantity that meets customer requirements. All decisions times related to suppliers selection will result in increased costs for the period. However, assignment cost at suppliers ***s*** become higher, approaching the end of the period.

Each sub-period correspond to the refresh time of parameters of our problem. The changing nature of information means that it is possible to adapt the supply chain after the initial configuration. In other words, adaptation in this case is trigged to meets the customer's request by a set of suppliers with the least cost.

In this context, decision variables are expressed as follow:

- V_s^δ: Supplier assignment at sub-period δ
- Q_s^δ: Quantity of product shipped from supplier s at sub-period δ

The formulation (1-5) presents the case where data is known in advance. Nevertheless, it can be applied to the case of a single sub-period.

$$Min\ Z = \sum_{s\in S}\sum_{\delta\in\Delta}[Cu_s^\delta.Q_s^\delta + Ca_s^\delta.V_s^\delta] \tag{1}$$

Subject to,

$$\sum_{s\in S} Q_s^\delta = D \qquad \forall\delta\in\Delta \tag{2}$$

$$Q_s^\delta \leq k_s^\delta.V_s^\delta \qquad \forall s\in S \qquad \forall\delta\in\Delta \tag{3}$$

$$V_s^\delta \in \{0,1\} \qquad \forall s\in S \qquad \forall\delta\in\Delta \tag{4}$$

$$Q_s^\delta \in \mathbb{N} \qquad \forall s\in S \qquad \forall\delta\in\Delta \tag{5}$$

This formulation involves minimizing the total cost corresponding to unit cost of product at supplier s for entire sub-period and assignment cost for each supplier for the same period. Eq.2 ensures the satisfaction of the demand at each sub-period. Eq.3 denotes the capacity restriction for each supplier.

We can prove that this problem is NP-hard considering a special case of this problem where $Cu_s = 0$ and $\Delta = \{1\}$. In this case, the problem can reduce to the formulation (6-8) which corresponds to a knapsack problem with a change of variables $X_s = 1 - V_s$.

$$Min\ Z = \sum_{s\in S} Ca_s.V_s \tag{6}$$

subject to,

$$\sum_{s\in S} k_s.V_s \geq D \tag{7}$$

$$V_s \in \{0,1\} \tag{8}$$

This formulation correspond to an integer linear program and thus we could try to solve it with a solver. However, giver the dynamic nature of data and taking into account the short time available to solve this NP-hard problem between the acquisition of the new costs and the decision of change, an approximate solution seems to be useful for solving this problem.

4 SUGGESTED APPROACH

4.1 A Dynamic Approach

In the recent years, dynamic optimization has been successfully used in many areas. Results have demonstrated the greater ability of this method to deal with problems subject to various disturbances.

Several definitions related to dynamic optimization are proposed in the literature. Among the most cited, a general definition is given by (Cruz et al., 2010). According to them, Dynamic optimization problem is a problem where the objective function or the restrictions change over time and where the occurrence of changes are unknown. The goal of the issues dealing with dynamic optimization problems is no longer to locate a stationary optimal solution, but to track its movement through the solution and time space as closely as possible (Lepagnot et al., 2010).

Generally there is not much time between two subsequent decisions time, restarting optimization at every changes is often undesirable. However, tracking optima is not enough. Decision taken now affects directly the future. The lack of visibility known by the term of "myopia" does not allows to predict the behavior of the models to the end of a given period. In other words, since the dynamic changes are unknown beforehand the problem has to be solved over time.

Inventory management and dynamic vehicles routing problem represent the two most studied in industry. A dynamic variant of the VRP is that the rides of different vehicles from a central repository are represented by cycles whose correspond to customers. The dynamic nature of this problem is that customers can be added or removed unexpectedly (Pillac et al., 2013). Inventory management problems are also treated in a dynamic context. Decision related to this case faces the problem of which quantity of products to command to maximize profit and when we decide to ship this quantity (Bosman, 2007).

Evolutionary Algorithms have been widely used to solve dynamic optimization. Given the continuous nature on data in real world, the moving peaks benchmark are proposed like test problems to compare the performance of these evolutionary algorithms. In our problem sub-periods allow optimization over time based on a small sequence of period when changes can occur. Hence, the optimum position may changes over time, the idea is to follow it in order to decide how to change the set of suppliers during sub-periods.

The literature review of (Nguyen et al., 2012) listed approaches dealing with changes in several issues :

- Detecting changes
- Introducing diversity when changes occur
- Maintaining diversity during the search
- Memory approaches
- Prediction approaches
- Self-adaptive methods
- Multi-population approaches

Our algorithm is based on approaches dealing with memory, introducing and maintaining diversity and self-adaptive methods. The principle is to use a population that is constantly conducting research to explore space research and ensure the diversification of solutions. The best optima found are stored in memory, in order to accelerate the convergence of the algorithm and follow the optimum whenever a change appears in the objective function.

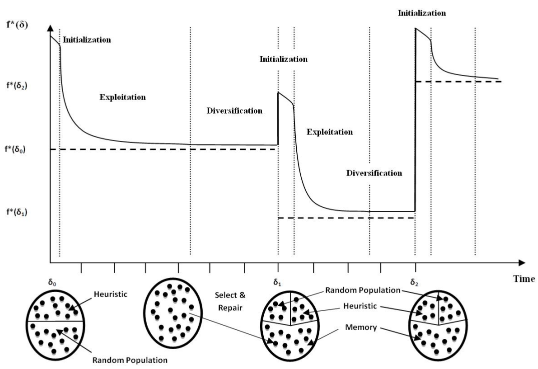

Figure 1: Algorithm behavior during time.

Three main phases are illustrated in Figure 1: Initialization, exploitation and diversification.

At $\delta = 0$ population is initialized based on two parts. A first part initialized randomly and the second is determined using the following heuristic.

G_j denotes the quantity of the gene j for each individual. k_j denotes the capacity of a supplier. D represents the total demand of the customer. Solutions are given based on this algorithm.

$\forall j \in 1...J$

$$R_j \leftarrow 0 \quad (9)$$

$$P \leftarrow D \quad (10)$$

While $(P > \sum_j R_j)$

$$j* \leftarrow \underset{j|G_j=0}{\text{argmin}} \quad \{Cu_j\} \quad (11)$$

$$G_{j*} \leftarrow 1 \quad (12)$$

$$R_{j*} \leftarrow k_{j*} - G_{j*} \quad (13)$$

$$P \leftarrow P - 1 \quad (14)$$

End while

While $(P > 0)$

$$j* \leftarrow \underset{j|G_j>0}{\text{argmin}} \quad \{Ca_j\} \quad (15)$$

$$Q \leftarrow min\{R_{j*}, P\} \quad (16)$$

$$G_{j*} \leftarrow G_{j*} + Q \quad (17)$$

$$R_{j*} \leftarrow k_{j*} - G_{j*} \quad (18)$$

$$P \leftarrow P - Q \quad (19)$$

End while

An exploitation phase comes after highlighting the operations of the genetic algorithm. However during the sub-period, at some points the convergence should be nearly finished and an exploration phase is launched. The purpose of this step is to diversify the population when it approaches the optimum in order to use it in the next update of data. In other terms, in the next optimization. Taking into account these operations, at $\delta = 1$ initial population is composed of three parts. A first part which represent the best individuals from the previous sub period. The second part represents the solutions derived from the heuristic. And finally, the third part is generated randomly. This mechanism is true for any time of change during all the periods of supply.

4.2 A Genetic Algorithm

"Genetic algorithms are search methods based on principles of natural selection and genetics". They encode the decision variables of a search problem into "finite-length strings of alphabets of certain cardinality". The strings which are candidate solutions to the search problem are chromosomes, the alphabets are genes and the values of genes are alleles. (Goldberg, 1989).

Representation Scheme. We started with a population composed of random solution chromosomes and then evolves via iterations generations. For our optimization problem formulated in the last section, each solution is represented by a chromosome P_i. ***G*** genes are considered for each chromosome, where ***ns*** is the number of suppliers and it contains the quantity Q_s which represent the quantity delivered by a supplier ***s***.

Initialization. The initialization is important in the performance of any Genetic Algorithm. An heuristic is used here but usually doesn't permit to generate the whole initial population. A random algorithm is thus used to fulfill the population. Each quantity is assigned randomly in an interval which meet suppliers capacity without exceeding the total demand of the customer for each chromosome created satisfying constraints 2 and 3. Since the optimization problem is with non-negative solutions, all genes are constrained to non-negative integers in the genetic algorithm, satisfying constraint 5 as a result. When the population is formed, all chromosomes should be evaluated by computing their fitness value one at a time. The evaluation fitness is the same as the optimization model defined in function 1

Selection. The selection of the valuable chromosomes that will survive and be passed to the next generation is extremely important. In our genetic algorithm, fitness proportionate selection is employed. In this method each individual in the population is assigned a roulette wheel slot sized in proportion to its fitness. We begin by evaluating the fitness f_i of each individual in the population. After we calculate the probability p_i corresponding to slot size.

Genetic Operations. The genetic operators used in the proposed genetic algorithm are crossover and mutation. Generally, among candidates selected for crossover, we choose chromosomes with probability p_c. For our case, we use a simple crossover operation in which a random crossover point ***k*** is determined, and a second part of the two selected individuals are exchanged. We use two chromosomes for an adaptable crossover to cope with demand constraint. Let's denote ***P1*** and ***P2*** the individuals selected for this operation in order to have two offspring ***E1*** and ***E2***. To fill the genes without exceeding the demand in E1 and E2, the following formula are used:

$\forall j \in 1....k$

$$E_{1j} = P_{1j} \qquad E_{2j} = P_{2j} \tag{20}$$

$\forall j \in k+1....ns$

$$E_{1j} = \begin{cases} \left[\frac{\sum_{k+1}^{ns} P_{1j}}{\sum_{k+1}^{ns} P_{2j}} \times P_{2j}\right] & : \sum_{k+1}^{ns} P_{2j} \neq 0 \\ \sum_{k+1}^{ns} P_{2j} / ns - k & : otherwise \end{cases} \tag{21}$$

$$E_{2j} = \begin{cases} \left[\frac{\sum_{k+1}^{ns} P_{2j}}{\sum_{k+1}^{ns} P_{1j}} \times P_{1j}\right] & : \sum_{k+1}^{ns} P_{1j} \neq 0 \\ \sum_{k+1}^{ns} P_{1j} / ns - k & : otherwise \end{cases} \tag{22}$$

Note: Brackets are used for the Rounding of certain value after the calculation of the quantity for crossover.

To illustrate the example, we use two chromosomes composed from 5 genes corresponding to the quantities of 5 suppliers. The sum of these quantities is equal to 50, in our case, referring to the demand D of the customer. See Figure 2

$$E_{13} = \left[\frac{P_{13} + P_{14} + P_{15}}{P_{23} + P_{24} + P_{25}} \times P_{23}\right] = 20 \tag{23}$$

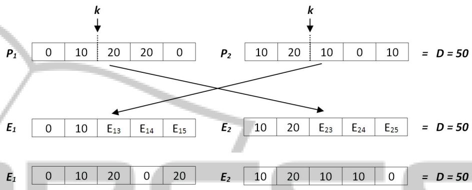

Figure 2: Example of crossover operator.

For the mutation, a transfer of a quantity between two genes selected randomly is assumed. In addition, the transmitter gene is randomly selected to provide the quantity to the other one. Figure 3.

Due to the capacity of suppliers. Individuals are subject to not deal with the total demand of the customer after crossover and mutation. For this reason, we have to repair each solution to cope with the demand constraint. In our case, the reparation of our individuals is inspired from the method that we have defined in section 4.1 dealing with the proposed heuristic. Indeed, instructions 9 and 10 are subject to be replaced. We begin by calculating the residual quantity r_j which is equal to the difference between the supplier capacity k_j and the quantity G_j (Formula 24). The aim is to compare the sum of the residual quantity r_j and P which present the quantity we dispose for reallocation (Formula 25). While this quantity exceeds the sum of r_j we should choose other suppliers to dispatch the quantity without exceeding the capacity of the selected supplier. This selection is based on the quantity of product available at the supplier which should equal to 0 and the cheapest one of them according to the assignment cost Cu_j and so on (Formula 11).

$$\forall j \in 1...J \qquad R_j = \begin{cases} k_j - G_j & : G_j > 0 \\ 0 & : otherwise \end{cases} \tag{24}$$

$$P = \sum_{j|R_j<0} -R_j \tag{25}$$

$$\forall j | R_j < 0 \qquad R_j \leftarrow 0 \tag{26}$$

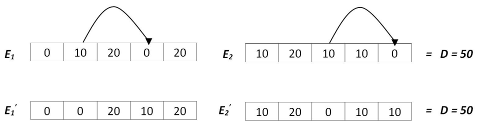

Figure 3: Example of mutation operator.

5 CONCLUSIONS

In this position paper, we rely on a two echelon supply chain problem dealing with a supplier selection issue in order to resolve it based on an Evolutionary Algorithm adapted to dynamic optimization. Our aim is to find a response for how to change the set of suppliers during time. Based on the optimum behavior after each change, we proceed to select suppliers for each sub-period. Given the dynamic parameters of the problem and its complexity, the choice of a solver for the resolution may be inadequate for medium to large size problems. Hence, the choice to search for an approximate solution seems appropriate in this case. For further studies, we are planning to extend and implement the problem to make in consideration more operations on supply chain related to forecasts of orders, inventories and adding other actors (distributors, retailers, etc.). An algorithm-based memory that detects changes and keeps the best individuals over time can converge quickly to the best solution as it was demonstrated in many Benchmarks. In addition other approach adapted for dynamic optimization problem, like anticipation, need to be developed if we want to take into account further operations in a global supply chain.

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