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Decision Support Technique for Supply Chain Management

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In this paper, we propose a method for supporting decision makers in the domain of supply chain management. Our objective is the global optimization instead of optimizing independent subsystems of the supply chain. The method architecture is based on combination of the simulation and optimization techniques which includes a multi-objectives optimization module and a simulation module. The optimization module is based on genetic algorithms and the simulation module uses effective alternative designs proposed by strategic and tactic decisions to find global optimal solution using the optimal scheduling solution proposed by the genetic algorithm for operational decisions. The experimental results show the efficiency and the feasibility of the proposed approach.

Keywords: supply chain management, decision, decision support technique, simulation, optimization

1. Introduction

One of the most active topics in manufacturing research is the supply chain management; it is at the center stage of business performance of manufacturing and service enterprises [13, 28,45, 49]. A supply chain management is defined as the logistic and production processes of an enterprise or a network of companies composing the production chain of a given industry [40, 41]. Thus, a supply chain is viewed as a network of connected and interdependent organizational units that operate in a coordinated way to manage, control and improve the flow of materials and information originating from the suppliers and reaching the end customers, after going through the procurement, processing and distribution subsystems of a company. The aim is to combine and evaluate from a systemic perspective the decisions made and the actions undertaken within the various sub-processes that compose the logistic system of a company [47]. This process integrates operations of the supply chain, even to the point of incorporating parts of the logistic chain that are outside the company, both upstream and downstream.

The integrated logistic process is used to attain an optimized supply chain, by minimizing a function expressing the total cost of processing, transportation (for procurement and distribution), inventory and equipment costs [6, 9]. Note that the optimization of the costs for each single phase does not generally imply that the minimum total cost of the entire logistic process has been achieved [19]. The main objective of this global optimization is to have models and computerized tools for planning and analysis to face the high complexity of current logistic systems (which operate in a dynamic and truly competitive environment) [12]. These logistic systems belong to manufacturing companies that produce a vast array of products and usually rely on a multi-centric logistic system, distributed over several plants and markets.

The perspective is therefore to devise an optimal logistic production plan, to minimize the total cost, which is the sum of procurement, processing, storage, distribution costs, in addition to the penalty costs associated with the failure to achieve some certain predefined services levels. However, to be implemented in practice, an optimal logistic production plan should be able to meet the physical and logical constraints imposed by limits on the available production capacity, specific technological conditions, the material costs, the configuration of the logistic network, minimum production lots, as well as any other condition imposed by the decision makers in charge of the planning process.

Because of the inherent complexity of decision making process in supply chains, there is a growing need for modeling methodologies [8, 20, 32] that can help identify and implement strategies for designing high performance supply chain networks. Some of the important reasons for the complexity of the decision making process are large scale nature of the supply chain networks, hierarchical structure of decisions, randomness of various inputs and operations, and dynamic nature of interactions among supply chain elements [8]. Optimization has recently become a high technology in supply chain planning and management [9, 10, 27]. The latest advancements in integrating optimization technology with evaluation techniques that model the complex supply chain environment have contributed to enabling improved and more focused decisions by the diverse set of managers involved in extracting the most value from the supply chain [34]. Expected benefits from these improved decisions include: increased throughput, reduced inventories, lower supply chain costs, increased return on assets, greater customer satisfaction, and reduced lead times.

The objective of our work is to give an optimization environment based on combination of the mathematical methods (for optimization) and simulation (for evaluation), to globally optimize supply chain designs. A model is a set of assumptions about the behavior of a system. These assumptions take the form of mathematical or logical relationships. If the relationships that compose the model are simple enough, it may be possible to use mathematical methods to obtain exact information on questions of interest; this is called an analytic solution. However, most real-world systems are too complex to allow realistic models to be evaluated analytically, and these models must be studied by means of simulation [26, 39]. Computer simulation models are used extensively as models of real complex systems to evaluate their output responses to certain stimulus [5]. One of the disadvantages of simulation historically is that it was not an optimization technique. In most studies, several search algorithms have been linked with the simulations, the genetic algorithms showed the capability to robustly solve large problems [2, 7, 25], that is why we propose an approach which uses the optimization based simulation.

On the other hand, mathematical optimization models [10, 27] represent a powerful and versatile conceptual paradigm for analyzing and solving problems which arise within integrated supply chain planning, and for developing the necessary software. They enable the development of realistic mathematical representations of a logistic production system, able to describe with reasonable accuracy the complex relationships among critical components of the logistic system, such as capacity, resources, plans, inventory, batch sizes, lead times and logistic flows, taking into account the various costs. Moreover, the evolution of information technologies and the latest developments in optimization algorithms mean that decision support systems based on optimization models for logistics planning can be efficiently developed.

Modeling and analysis of supply chains to gain a better understanding of their complexity and to predict their performance are critical in their design stage, and often valuable for their management. We present a general framework to support the decisions for supply chain networks using a combination of optimization and simulation techniques. The solution given by the optimization model is translated into decision rules that are evaluated by the simulation. This procedure is applied iteratively until the difference between subsequent solutions is small enough. This method is applied successfully to several test examples and is shown to deliver competitive results. It provides the possibility to model and solve more realistic problems (incorporating dynamism and uncertainty) in an acceptable way. The limitations of this approach are given as well.

The rest of this paper is organized as follows. In Section 2, we present issues and challenges in supply chain. We concentrate on decisions types and on how we measure their performance. Section 3 will present in detail our approach that is based on defined architecture combining simulation and optimization methods for supply chain global optimization. In Section 3, we present an implementation and some experiment results with a discussion. This paper is concluded by remarks and perspectives.

2. Issues and Challenges in Supply Chain Management

We define a supply chain as a network of facilities (organizations, people, technology, activities, information, resources and distribution options) that performs the functions of procurement of materials, transformation of these materials into intermediate and finished products, and the distribution of these intermediate/finished products to customers [12]. All these facilities are used for fulfilling a customer request. The challenges of supply chain are to produce the right products, in the right quantities, at the right place, at the right moment and at minimal cost.

Figure 1 shows an example of a supply chain. Materials flow downstream, from raw material sources through a manufacturing level transforming the raw materials to intermediate products. These are assembled on the next level to form products. The products are shipped to distribution centers and from there on to retailers and customers.

2.1. Decisions in supply chain management

Supply chain management decisions have been classified based on two main dimensions, according to their nature of organization and scope for development. Each dimension has three classes (points), giving a total of nine possible combinations. According to their nature of organization, decisions can be classified as structured, unstructured or semi-structured [22, 23]. A decision is structured if it is based on a well-defined decision-making procedure that can be represented by an algorithm which is suited for automation. A decision is said to be unstructured if the elements of the system cannot be described in detail and reduced to a predefined sequence of steps to produce decisions systematically. A decision is semi-structured when some elements are structured and others are not. Scope for developing supply chain decisions can be classified into three classes: strategic (long-term), tactical (medium-term), and operational (short-term and real-time) [8] There are four major functional areas in supply chain management: procurement, manufacturing, distribution, and logistics [6, 41]. In addition, there are also certain global areas whose scope extends over multiple functions. These functional areas can be structured, unstructured or semi-structured. There are strategic, tactical, and operational decisions in each of these areas [12].

On the strategic level, long term decisions are made. Decisions are strategic when they affect the entire organization (the whole areas) or at least a substantial part of it for a long period of time. The general objectives and policies of an enterprise are strongly influenced by the strategic decisions [12]. As a consequence, strategic decisions are taken at a higher organizational level, usually by the company top management. The strategic decisions are related to location, production, inventory, and transportation. Location decisions are about the size, number, and geographic location of the supply chain entities, such as plants, inventories, or distribution centers. The production decisions are meant

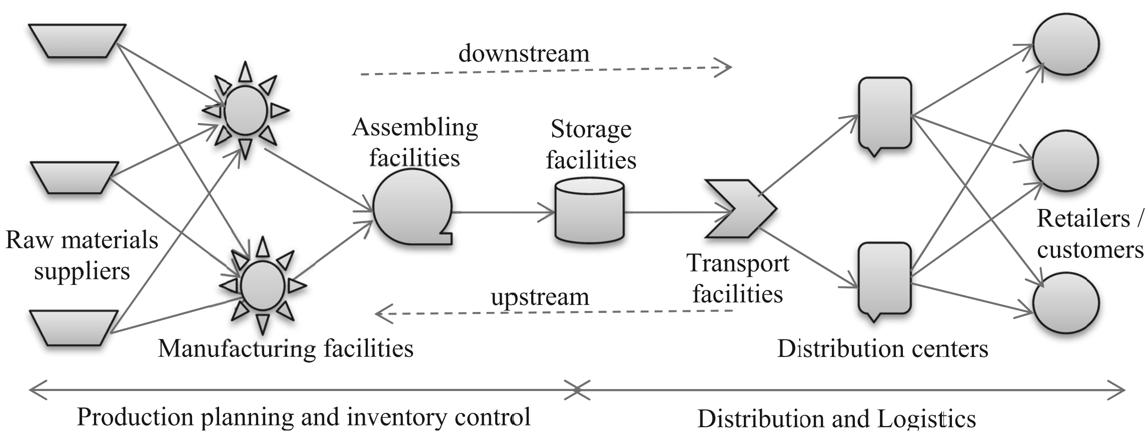

Figure 1. Supply chain example.

to determine which products to produce, the products quantity, where to produce them, with which plants, which suppliers (raw materials) to use, from which plants to supply distribution centers, and so on. Inventory decisions are concerned with the way of managing inventories throughout the supply chain. Transport decisions are made on the modes of transport to use. Decisions made on the strategic level are interrelated. For example, decisions on mode of transport are influenced by decisions on geographical placement of plants and warehouses, and inventory policies are influenced by choice of suppliers and production locations. Strategic decisions are usually unstructured decisions. Consequently, for analyzing these complex interrelations, and the impact of making strategic level changes in the supply chain, we use modeling and simulation by defining governing rules.

Tactical decisions affect only small parts of an enterprise and are usually restricted to a single department. The time span is limited to a medium-term horizon, typically up to a year. Tactical decisions place themselves within the context determined by strategic decisions. In a company hierarchy, tactical decisions are made by middle managers, such as the heads of the company departments. On the tactical level, decisions are made, from month to month, such as monthly demand forecasts, planning for distribution and transportation, production planning, and materials requirement planning.

Operational decisions refer to specific activities carried out within an organization and have a modest impact on the future. Operational decisions are framed within the elements and conditions determined by strategic and tactical decisions [47]. Therefore, they are usually made at a lower organizational level, by knowledge workers responsible for a single activity or task such as sub-department heads, workshop foremen, and back-office heads. The operational level of supply chain management is concerned with the very short term decisions made from day to day [18]. Usually, we don't distinguish between the tactical and operational levels. Their changes can be studied using either modeling and simulation or mathematical methods.

2.2. Supply chain performance measures

A metric is a standard of performance measurement. The metrics give the basis on which to evaluate the performance of processes in the supply chain. They help to follow the development of the supply chain [46]. The calculation of metrics uses collected relevant data and then the performance can be evaluated. A supply chain in which the appropriate data is not regularly collected cannot be properly managed. In connection with a decision-making process, it is often necessary to assess the performance of a system. For this purpose, it is appropriate to categorize the evaluation metrics into two main classes [6, 28]: effectiveness and efficiency. Effectiveness measurements express the level of conformity of a given system to the objectives for which it was designed. The associated performance indicators are therefore linked to the system output flows, such as production volumes, weekly sales and yield per share. Efficiency measurements highlight the relationship between input flows used by the system and the corresponding output flows. Efficiency measurements are therefore associated with the quality of the transformation process. For example, they might express the amount of resources needed to achieve a given sales volume.

The effectiveness and efficiency of a system are assessed using measurable performance indicators that can be classified into different categories. There are metrics to measure the effectiveness of various alternatives that correspond to the different kinds of system performance as economical, technical, and political criteria [12, 23]. The process of evaluating the alternatives may be divided into two main stages: exclusion and evaluation. During the exclusion stage, compatibility rules and restrictions are applied to the alternative actions that were originally identified. Within this assessment process, some alternatives will be dropped from consideration, while the rest represent feasible options that will be promoted to evaluation. In the evaluation phase, feasible alternatives are compared to one another on the basis of the performance criteria, in order to identify the preferred decision as the best opportunity. A rational approach to decision making implies that the option fulfilling the best performance criteria is selected out of all possible alternatives

[47]. Generally speaking, effectiveness metrics indicate whether the right action is being carried out or not, while efficiency metrics show whether the action is being carried out in the best possible way or not.

Once the alternative actions have been identified, it is necessary to evaluate them on the basis of the performance criteria deemed significant. Mathematical models and the corresponding solution methods usually play a valuable role for choosing the best alternative. For example, optimization models and methods allow the best solution to be found in very complex situations involving countless or even infinite feasible solutions. Supply chain performance measures can be classified into two categories [32]: qualitative measures (such as customer satisfaction and product quality) and quantitative measures (such as order-to-delivery lead time, supply chain response time, flexibility, resource utilization, delivery performance, etc.). The quantitative performance measures are the most useful for supply chain development. Quantitative metrics of supply chain performance can be classified into two broad categories: non-financial and financial.

Important quantitative metrics include: lead time, customer service level, inventory levels, resource utilization, and flexibility [32]. In addition to these, there are several fixed and operational costs associated with a supply chain. Ultimately, the aim is to maximize the revenue by keeping the supply chain costs low. Costs arise due to inventories, transportation, facilities, operations, technology, materials, and labor In the following, we present brief definitions of them.

Lead time is the end-to-end delay in a business process. For supply chains, the business processes of interest are the supply chain process and the order-to-delivery process. Correspondingly, we need to consider two types of lead times: supply chain lead time and order-to-delivery lead time. The order-to-delivery lead time is the time elapsed between the placement of order by a customer and the delivery of products to the customer. The supply chain process lead time is the time spent by the supply chain to convert the raw materials into final products plus the time needed to deliver the products to the customer.

Customer service level or the metric of satisfying customers (customer service) is the desired end result of any supply chain management strategy. Customer service level in a supply chain is a function of several different performance indices. The first one is the order fill rate, which is the fraction of customer demands that are met from stock. For this fraction of customer orders, there is no need to consider the supplier lead times and the manufacturing lead times. Another measure is the backorder level, which is the number of orders waiting to be filled. To maximize customer service level, one needs to maximize order fill rate, and minimize backorder levels. Another measure is the probability of on-time delivery, which is the fraction of customer orders that are fulfilled on-time, i.e. within the agreed-upon due date. The customer service metric depends on flexibility and inventory metrics.

We can define inventory levels as follows [46,48]. Manufacturing entities have inventories for raw products: Raw Products Inventory (RPI), products in the production process: Working Inventory Process (WIP), and finished products: Finished General Inventory (FGI). In addition, often there are warehouses or distribution centers between the different levels of the supply chain. Inventories are costly. It is desirable to avoid so-called dead inventory, i.e. inventory that is left when a product is no longer on the market. As we see, it is in every company's interest to keep inventory levels at a minimum. A main objective of the Just in Time (JIT) paradigm is to virtually abolish inventories.

Another important metric is the resource utilization. A supply chain network uses resources of various kinds [8]: manufacturing resources (machines, material handlers, tools, etc.); storage resources (warehouses, automated storage and retrieval systems); logistics resources (trucks, rail transport, air-cargo carriers, etc.); human resources (labor, scientific and technical personnel); and financial (working capital, stocks, etc.). The objective is to utilize these assets or resources efficiently so as to maximize customer service levels, minimize lead times, and optimize inventory levels. Flexibility can be defined as the ability to respond to changes in the environment. In the case of a manufacturer, flexibility is the ability to change the output in response to changes in the demand. Higher flexibility allows less level of inventory to maintain the same level of customer service.

3. Method for Global Optimization

In the following we will propose a method for optimizing the performance of supply chains. Our objective is to focus on global performance instead of optimizing performance of separate facilities as material procurement, manufacturing, or distribution. Optimizing facilities performance separately will only improve performance in each facility, but the complex interaction among supply chain facilities is ignored. Integration and coordination are keys for improving the global performance. Integrating supply chain facilities means that each facility will have access to information relevant to its task and will understand how its actions will impact other components, thereby enabling it to choose effectiveness alternatives that optimize the supply chain's objectives. The integrated components should coordinate to manage dependencies among activities so as to achieve coherent operation of the entire supply chain.

Recently, there is an increasing focus on the integration of different facilities of the supply chain, as for example integration and coordination of production and distribution functions [21, 3, 4]. But our concentration is about a general coordination where the integration of different functions can be realized, e.g. inventory and production planning, sales, and distribution. Another level of coordination we are considering is about production, where decisions are coordinated among the plants (multi-plant coordination) of an internal supply chain. The objective of multi-plant coordination is to coordinate the production plans of several plants in an integrated manufacturing company so that the overall performance of the company is improved. In order for such coordination to be efficient, the effects of uncertainty of final demand, uncertainties in production process at each plant, and capacity constraints at each plant must be taken into consideration [13].

Before presenting our approach in detail, it is important to present useful concepts. A job is processing of a client order to produce a specific quantity of an item with a specific start and/or due dates. An operation is a discrete step or task, one of a number required to make an item. A workstation is a specific machine or employee work space. A work center is a machine grouping or work grouping used for scheduling and costing. A routing is a sequenced list of operations, with associated work centers. A loading is assigning jobs to work centers. The performance measures are based essentially on Job Flow Time (time at a workstation, work center, or plant), Average Flow Time (group of jobs: Sum of flow times for n jobs$/n$), Job Lateness (expected due date – original due date), Makespan (group of jobs: from start of first job to end of last job), and Average Number of Jobs (group of jobs: total flow time/Makespan).

Our problem is to optimize the performance by satisfying the clients at low costs. We seek to develop a solution to this problem through the satisfaction of constraints on the arrival dates of materials and delivery dates for finished products, all these with maximizing production profits. The goal is to coordinate structural organizations at strategic level, products quantities at tactical level, and just in time schedules at operational level within the overall system of production to fulfill orders and minimize the costs associated with respect to fixed dates. At the operational level, we use just in time scheduling, where the release dates and due dates are negotiated with external suppliers and external customers, respectively. All these dates are controlled by the decisions taken at the level of planning. The (soft and hard) release dates are associated with the first operation of each job and the (soft and hard) due dates are associated with the last operation of each job. In other words, we attempt to search global optimization by optimizing resources and their organization at the strategic (conceptual) level, optimizing and controlling just in time schedules using some planning tactics (as changing products quantities).

3.1. Objectives and architecture of the method

The overall objective is to give an optimal supply chain design. A model is a set of assumptions about the behavior of a system. These assumptions take the form of mathematical or logical relationships. If the relationships that compose the model are simple enough, it may be possible to use mathematical methods (such as algebra, calculus, or probability theory) to obtain exact information on questions of interest; this is called an analytic solution. However,

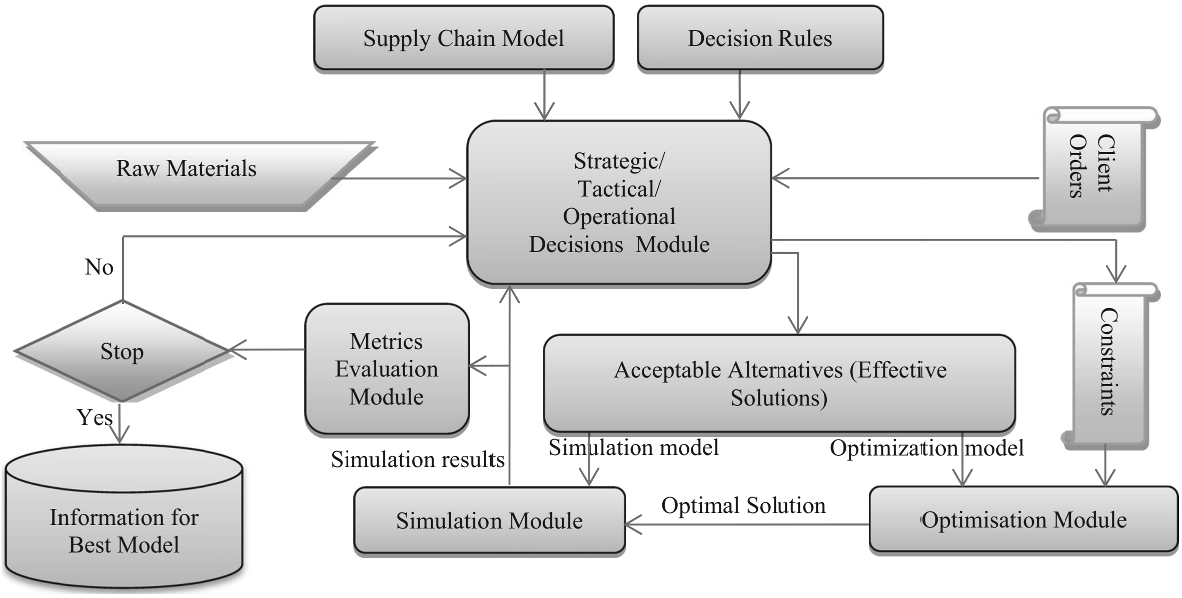

Figure 2. Method architecture.

most real-world systems are too complex to allow realistic models to be evaluated analytically, and these models must be studied by means of simulation [46].

Today's uncertain and dynamic business environment creates opportunity and risk. Supply chain optimization is most useful in situations where a company or a product has a complex supply base, a complex manufacturing process, a complex distribution system, and volatile demand [35] Essentially, whenever there is uncertainty in the behavior of supply chain operations or in market demand, supply chain optimization could benefit the company [24]. However, the real challenge of supply chain management stems from the uncertainty that is inherent in everyday events at every point in the chain, for example [35]: (1) Forecasts of customer demand are seldom accurate and often misleading, (2) Manufacturing is vulnerable to technical problems, and (3) Distribution can suffer from freight delays. It is paramount to develop models for supply chain that take into account the uncertainty and complexity.

The suggested solution is based on the architecture shown in Figure 2. The overall architecture contains a supply chain model for describing the network structure which is composed of facilities used in the supply chain. This model will pass this structural information to strategic, tactical and/or operational decisions module. The former has access to other information from external raw materials suppliers as delivery times and from external clients as orders and their due dates. This module, based on decision rules, will propose uncertain strategic, tactical, and operational decisions for the supply chain architecture, taking into account its structure described in the supply chain model, as its restructuration by reducing for example, the number of involved resources.

Thus, the decision module will filter all alternative solutions to effective and non-effective solutions based on knowledge (economical, technical, etc.) rules and other information from raw materials suppliers and client orders. The module outputs are effective solutions with operational constraints. The acceptable alternatives are described by uncertain (generic) models (using uncertain parameters values). These uncertain parameters are related to strategic, tactical and operational decisions.

At the strategic level, these uncertain parameters represent location, production, inventory, and transportation. Location uncertain parameters are about the size, number, and geographic location of the supply chain entities, such as plants, inventories, or distribution centers. The production uncertain parameters are meant to determine which products to produce, the products quantity, where to produce them, with which plants, which suppliers to use, from which plants to supply distribution centers, and so on. Inventory uncertain parameters are concerned with the way of managing inventories throughout the supply chain. Transport uncertain parameters are made on the modes of transport to use. At the tactical level, the uncertain parameters are about monthly demand forecasts, planning for distribution and transportation, production planning, and materials requirement planning. Thus, the tactical information is planning information as decisions on products quantities, resources use, etc. At the operational level, these uncertain parameters represent, in particular, the shop design (flow shop or job shop), jobs/materials quantities and temporal/resources constraints.

The acceptable alternatives description is partitioned to two uncertain models (optimization and simulation models), which are inputs to two modules. The first module is the optimization module. With a set of constraints, this module will generate an optimal scheduling solution for operational decision. In its turn, the optimal scheduling solution with the simulation model will be inputs to the second module, which is the simulation module. The raison behind the use of combination of two modules (optimization and simulation) is due to the complex behavior of supply chain [26, 39]. Thus, a process of behavior partition of the supply chain model to two sub-models is necessary to gain profit from analytical methods and simulation methods.

At the beginning, initial values for uncertain parameters are given by the user via the decision module. This module will check these values against the decision rules and constraints information from raw materials suppliers and client orders. Then, the optimization module is asked to produce the optimal scheduling using its uncertain model (described with uncertain parameters values), temporal and resources constraints. After this, the simulation module will simulate the uncertain simulation model using the optimal scheduling sequence. The simulation results will be used to evaluate the global performance of the proposed alternative decision by measuring different metrics. If the global performance is less than a satisfaction criterion, the simulation results will be passed to the decision module to feed the decision rules for proposing other values for uncertain parameters of the supply chain model. This process will continue until reaching a stable state or a fixed maximum number of iterations is realized. A decision maker can be satisfied by the best solution found so far and, as a consequence, he will stop the research process of founding other solutions.

The objectives of this method are to propose an effective supply chain model with high performance. High performance model minimizes resource use to reach specific outcomes, whereas effectiveness is the ability of facilities to deliver products or services in a manner that satisfies end-users. Performance is measured by delivery time, product quality, number of short orders, and inventory levels, whereas effectiveness is measured by service quality the service needs of the focal firm and the focal firm's customers.

We will use modeling to describe the relationships between decisions, constraints, and objectives. Models should capture the essence in order to obtain maximum result of the supply chain. These models can become very complex as well as detailed. Therefore attention must be paid in selecting the model that is suitable for the needs of the business. For modeling, a decision maker in a supply chain to take decisions should respond to questions like: when and how much of a raw material to order from a supplier, when to manufacture an order, when and how much of the product to ship to a customer or distribution center. Decision constraints are limitations placed upon the supply chain plan, a supplier's capacity to produce raw materials or components, a production center that can only run for a specified number of hours per day and a worker that must only work so much overtime, a customer's or distribution center's capacity to handle and process receipts.

The constraints can either be hard or soft. Hard constraints could be, for example, the number of working hours in a shift or the maximum capacity of a truck and they have to be satisfied [35]. Soft constraints, instead, can be relaxed or violated [24]. Examples of soft constraints include customer due dates or warehouse space limitations. In practical situations penalties are imposed if a soft constraint is not met. The penalties allow constraints to be weighted by importance. For example, missing a customer due date is a more important concern than cluttering a warehouse aisle. The objective of the decision maker could be one or a combination of the following: maximizing profits or margins, minimizing supply chain costs or cycle times, maximizing customer service, minimizing lateness, maximizing production throughput, satisfying all customer demand [35].

4. Functionality and Experimental Results

We will present more details about the functionality of this approach and some experimental results. For testing our approach a prototype is developed. As mentioned above, a supply chain model is partitioned to two communicating submodels: a simulation model that is an approximation of the complex behavior of the supply chain and an exact mathematical optimization model representing the rest of its behavior. The simulation module will run the simulation model using given uncertain parameters and a scheduling sequence as a set of stimulus and it will terminate when this scheduling sequence is expired. The simulation results will be used as information for measuring relevant metrics that can help decision makers to improve the supply chain. The code of the simulation module can visualize schedule process by showing the progress of jobs and performance by showing load and idle time for a machine or work center by time period. The simulation results are used by the decision module that uses predefined strategic, tactical and/or operational rules to restructure the supply chain model. These rules are defined by decision makers as a set of improvement rules.

On the other hand, scheduling is one of the most important decision-making processes in the area of production management (operational/tactical level) [1, 31]. It is aimed at efficiently allocating the available machines to jobs, or operations within jobs and subsequent time-phasing of these jobs on individual machines [37]. A schedule is composed of the following three major processes [44]: assignment, sequencing, and timetabling. Scheduling problems are generally very complex in nature due to their combinatorial nature. Traditional approaches to solve scheduling problems use simulation, analytical models, heuristics or a combination of these methods. A scheduling problem is a typical representative of a combinatorial optimization class of problems consisting of a set of jobs J, a set of resources M, a set of objectives F and a set of constraints C. A job J_j consists of a set of operations $\{O_{j(1)}, O_{j(2)}, \ldots, O_{j(oj)}\}$ with each operation $O_{j(i)}$ to be processed on a machine M_k.

A job J_j is a fundamental entity described in time domain by a release date, r_j (specifying the time before which no operation of the job can be processed) and due date d_j (the date at which the job is promised to be completed), that is executed for a processing time p_j on one or more resources/machines. The completion time of a job C_j, is the time by which all the operations of the job complete their executions on corresponding machines. A resource M_k is any physical or virtual entity of limited capacity and/or availability, allocated to the execution of jobs competing for it. A resource is generally used in the term of machine. A resource can be renewable and consumable; it can also be classified as cumulative or disjunctive. In our implementation, only renewable disjunctive resources are taken into account.

A solution of a scheduling problem must always satisfy the given constraints, it can be classified as temporal constraints and resource-capacity constraints [43]. Temporal constraints are generally related to execution window of a job (or operations) in time horizon, for example a job J_j cannot start its execution before r_j and must finish its processing before d_j. This constraint may be specified as $r_j \leq s_j \wedge C_j \leq d_j$ where s_j is the time at which the job starts its execution. Resource-capacity constraints specify the capacity and/or availability of a resource, for example, that no more than one operation can be executed at the same time on a resource of unit capacity.

The objectives reflect the characteristics desired in the final schedule. Different performance measures may be used for the evaluation of schedules in regard to the objectives under consideration. The most studied objective related to completion times is minimizing the completion time of the entire schedule, known as "makespan" and denoted as $C_{\max}$. It is defined as $C_{\max} = \max\{C_j | 1 \leq j \leq N\}$, where N is the number of jobs. Another very important function of due dates is "tardiness", which can be measured through several performance measures. The tardiness of a job j is computed as $T_j = \max(0, C_j - d_j)$.

Scheduling problems are typically described using the three-field notation $(\alpha|\beta|\gamma)$ [11]. The α field represents the machine environment (shop design). Production scheduling optimization modeling depends essentially on shop designs. There are three principal shop designs: flow shop, job shop, and open shop. The most used notations of α field are FS^m and JS^m, the first notation is for flow shop with m machines [29] (the flow shop scheduling problem consists of N jobs which require processing on m different machines, each job has a process sequence of m operations, this process is one and same for all jobs). The second notation is for job shop with m machines [15, 16, 38] (it's a flow shop problem but the process sequences of the jobs are different from one to another).

The field β indicates any additional constraints that might be present in our problem. For example: p_j^{stoch} (stochastic processing times), $d_j = d$ (common deadlines), r_j (release times). Without this constraint, we assume jobs are all released at time $t = 0$, and $prec$ (precedence constraints). Finally, γ indicates the objective. For example, $\min(C_{\max})$ (minimize makespan), $\sum_{j=1}^{N} T_j$ (minimize sum of tardiness).

We have integrated the NSGA-II (Elitist Non-dominated Sorting Genetic Algorithm) [14, 30, 33] to our prototype as the optimization method. The aim of this algorithm is to find a set of non-dominated solutions based on the Pareto dominance relationship. NSGA-II implements elitism and crowded tournament selection. Elitism is a mechanism that ensures the best-fit individuals in a population that are retained and thus one can be assured that good fitness obtained does not get lost in subsequent generations. Crowded tournament selection is a selection mechanism based on tournament selection whereby, a group of individuals takes part in a tournament and the winner is judged by the fitness levels (a combination of rank and crowding distance) that each individual brings to the tournament.

For experimenting with our developed prototype, we have defined a simple supply chain model. This model contains two production stages. The first is composed of two parallel production lines, and the second is composed of one line for assembling. Every production line will be composed of a number of machines with different speeds and qualities, thus with different costs. There are feeding and storing inventories for each production line with different capacities. The raw materials are provided from three different suppliers. Each raw material has a quality level; a poor quality will require more resources for preprocessing, but it has fewer constraints as release time.

The client orders are used to determine the jobs to realize, the temporal and resources constraints, and the shop design to use. There is a set of defined rules to determine the number of resources, their speed, which raw materials to use, etc. The rules set will be executed up on the simulation results as their inputs. The simulation results are about how the resources are exploited for a particular uncertain supply chain structure with a scheduling sequence (for example, if a resource is used less than expected, it can be removed from the resources list), if the raw material quality is not influencing the temporal constraints, or if the inventories levels are sufficient, and so on. We have realized two types of simulation (this depends on client orders), one is for flow shop design (Figure 3) and the other is for job shop design (Figure 4).

Flow shop scheduling is one of the most important problems in the area of production management [17, 29]. It can be briefly described as follows: All jobs have to follow the same route i.e., they have to be processed first on machine 1, then on machine 2, and so on. There are no precedence constraints among operations of different jobs, operations cannot be interrupted and each machine can process only one operation at a time.

Figure 3 shows simulation results for 10 proposed supply chain model designs by the decision module. Each result is dependent on a model and is composed of resources cost, raw materials cost and tardiness of scheduling sequence solution as proposed by optimization module. The resources cost is the total cost of machines and facilities used in a model, including inventories. We have defined an evaluation metric to choose the best model, which is as follows:

$$\begin{aligned} ModelMetric =& resourcesCost \\ &+ rawMaterialsCost \\ &+ 0.2 * Tardiness \end{aligned}$$

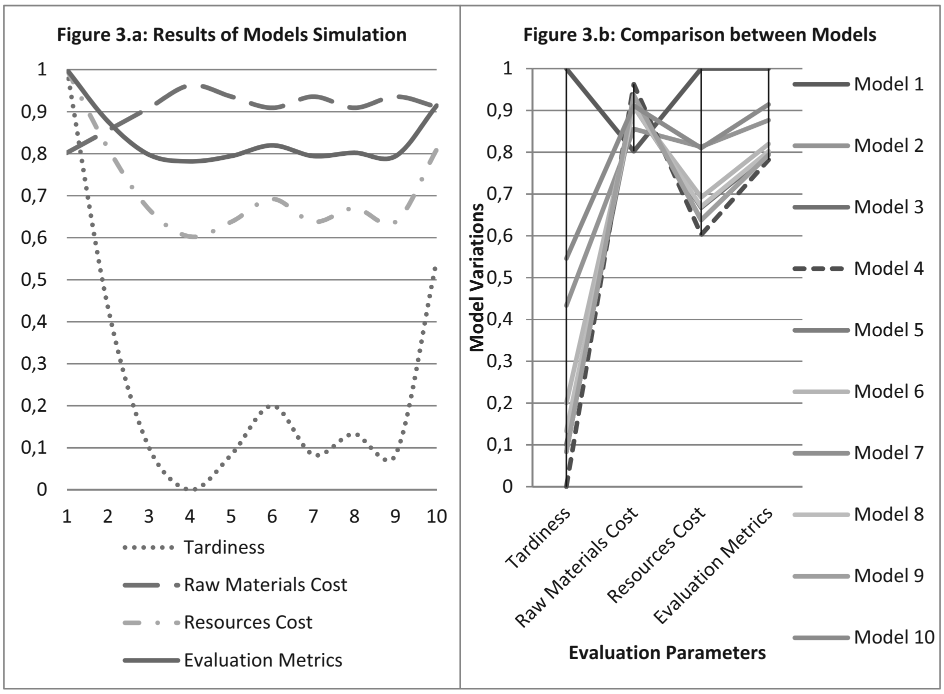

Figure 3. Results for flow shop design.

From these results, model number 4 (dashed lines) is the best, which has zero time of tardiness, high cost of raw materials, it uses the best quality of raw materials, and has influence on resources costs, as explained above. The results show that the model also has the lowest cost of resources.

Figure 4 shows results for job shop problem, where any job is composed of a different number of operations. Any successive operations of the same job are processed on different machines. The execution of each operation of a job requires one machine out of a set of given machines and a process time for each alternative

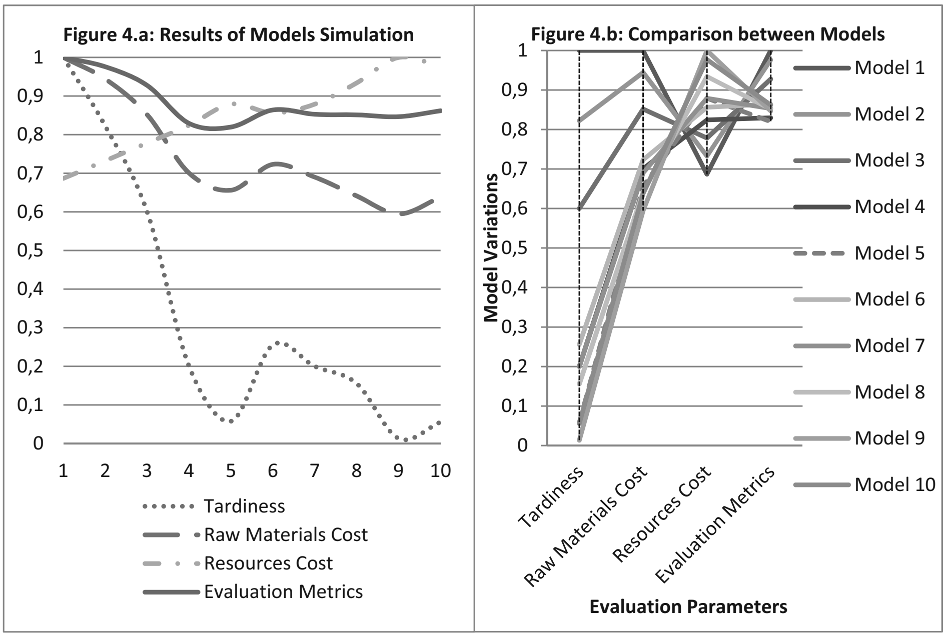

Figure 4. Results for flow shop design.

machine [36, 42]. Each machine determines the sequence of the assigned operations on it. Precedence constraints are imposed on the order of operation processing.

The results illustrated in Figure 4 show model number 5 (dashed lines) as the best model. Although model number 9 has less time of tardiness and thus better performance, according to the specified metric, it has less profit than model number 4.

5. Conclusion

In this work, we have presented a decision support system based on simulation/optimization techniques to optimize supply chain planning by determining a feasible plan that meets all demand needs and supply limitations, optimizing the plan in relation to corporate goals such as low cost and profitability. The time taken by the decision support to process the models can vary significantly with the dimension and the complexity of the model. This technique provides significant improvement in the performance and insight into the supply chain system, without the investment of much money. Simulation/Optimization benefits the business and profitability in many ways. It generates solutions faster automates the solution process and verifies that the solution adheres to your business rules, dramatically improves business flexibility, responsiveness to changing circumstances, and ability to test different scenarios, focuses decisions and resources on business priorities.

Our decision support system can provide three types of solutions: (1) Feasible solutions that satisfy all the constraints of the problem. (2) Optimum solution that is the best feasible solution that achieves the objective of the optimization problem. Although some problems may yield more than one feasible solution, there is usually only one optimum. (3) Optimized solution that partially achieves the objective of the optimization problem. It is not the optimum or best solution, but it is a satisfying or reasonable one. This is usually one of the best feasible solutions. However, for optimization problems that have no feasible solutions, it may be one of the best infeasible solutions. For example, in a resource-constrained environment, it may be a solution that is infeasible because it does not meet all customer due dates, but it may minimize operating costs. In the future, we intend to complete this work to cover most aspects of supply chain systems that can help us to test this approach further and prove its value.

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