Oil Industry Supply Chain Management as a Holonic Agent Based Distributed Constraint Optimization Problem

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Abstract. Very few industries can benefit more from maximizing supply chain efficiencies than the oil and gas companies. However, the behavior of such supply chains is too complex to be modeled analytically. Multi-agent systems show great similarity with respect to supply chains and provide the flexibility to model the complexities and dynamics of real world supply chains without excessive simplifying assumptions. Since supply chain management problem has a recursive structure, it becomes appropriate to employ holonic agents for its modeling. In addition, the type of relationships between its entities and the required global optimization make it natural to model its interactions as constraints, and the entire system as a Distributed Constraint Optimization Problem (DCOP).

1 Introduction

Supply chain management can be defined as the configuration, coordination and continuous improvement of an organized set of operations. Its goal is to provide maximum customer service at the lowest cost possible, where a customer is anyone who uses the output of a process. Since the goal of a company is to maximize profits, it must weigh the benefits versus the costs of its decisions along the supply chain. Very few industries can benefit more from maximizing supply chain efficiencies than the oil and gas companies [2]. In this industry, there is a need to ensure that each entity along the supply chain can respond quickly to the exact needs of its customers. On the other hand, one of its weaknesses is that each entity is likely to act in its best interests to optimize its own profit. In general, that doesn't meet the goal of the entire supply chain. Integrating the management decisions of different parts of the supply chain may provide huge gains and benefits, which are usually concealed by the pitfalls of short-term and local angles. Historically, the decisions of business supply chains have been highly concentrated, and researchers have used analytical approaches focusing on how to improve the efficiency of the individual entities along the chain instead of improving its combined performance. Although, in general, great corporations own a global planning application that tries to take into account the main activities and goals of its components, the complexity of the resulting system makes it unfeasible an integration of these latter. In addition, even if the centralized planning system is simple enough to work, the frequent and unforeseeable changes in the business environment render its results obsolete and useless very fast. Since multi-agent systems show great similarity with supply chains, multi-agent systems become a suitable means to manage the supply chain with a better performance than that attained by the current human-software approach. Furthermore, the recursive nature of supply chains suggests the use of holonic agents, which are fractal structures that deal better with the communication between different abstraction levels of the supply chain. Finally, the distributed constraint optimization formalism fits very well to the supply chain management problem, which is naturally distributed but tightly coupled as a network of facilities. This approach makes the local and selfish nature of the agents meet the requirement of a global optimization. They do so using only local communication with neighboring agents, since for such problems communication with a single central agent is unacceptable. In addition, it allows agents to operate in an asynchronous and more efficient way.

This paper proposes a preliminary model that includes both holonic agents and distributed constraint optimization for the oil industry supply chain management. The next section synthesizes the basic concepts involved in the work. Section 3 describes the problem in focus, and the section 4 presents the proposed model, which is divided into an organization model and a constraint optimization model, which are then refined to a distributed constraint optimization model. Finally, the paper concludes with a summary of the current results, and an outlook on future research activities.

2 Basic Concepts

2.1 Oil Supply Chain

A typical oil industry supply chain includes exploration of new petroleum (crude oil) reservoirs, drilling of crude wells, crude extraction at onshore and offshore platforms, its transport to the refineries, the refining of the crude oil (raw material) in the refineries in order to produce the final products (petroleum derivatives), such as gasoline and diesel, the transport of those products to distribution terminals where they are dispatched to distribution companies, and finally the delivery of the derivatives to the final customers (e.g. gas stations). There are different types of crude, with distinct qualities. Each of them has a specific production profile, yielding definite proportions of each derivative product. As to the transport of crude and its derivatives, it is carried out by ships, trains, trucks, and mainly by pipelines.

Oil supply chain management is intrinsically associated with integrated planning. First, it is concerned with functional integration of acquisition of raw material (crude oil), manufacturing (refining), transportation, and warehousing activities [9]. In the oil industry supply chain, that integrated planning links fundamental processes, like

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logistics (responsible for transportation planning), production management (oil extraction and refinery production planning), inventory management (hedge against the uncertainties of supply and demand, or reserve for seasonal demand), and demand forecasting (statistical prediction of future demand for final products). The goal of the inventory management is to determine the trade-off for the inventory levels, so that they are not too low that lead to lose opportunities, or too high that impose useless inventory hold costs. The usual way to attain this goal is to use either probabilistic analytical models or simulation.

An important component in supply chain analysis is the choice of performance measures, which are used to determine the efficiency of a system, or to compare alternative ones. The literature categorizes these measures as either qualitative or quantitative. In general, quantitative measures are related to monetary values, as cost and profit, whereas qualitative ones are based on customer satisfaction [1]. Traditionally, mathematical optimization models are used to solve supply chain management problems; however, supply chains are too complex to allow realistic models to be evaluated analytically**.**

2.2 Multi-Agent Systems (MAS)

MAS offer such useful features as parallelism, robustness and scalability. They are highly applicable in domains where centralized approaches meet their limits, and are composed of autonomous, reactive, proactive, and interacting entities called *agents*, engaged in the realization of a joint goal. Negotiation is a fundamental capability of agents to reach their goals. The agent-based framework may lead to more effective integration of production, logistics, and trading processes. Agent descriptions provide an ability to specify both static and dynamic characteristics of various supply chain entities [11]. Since a supply chain is a network of facilities, each agent can be assigned to model a facility, and relationships can be defined as links to connect these agents. An approach that considers the supply chain by means of agents and simulation is very well-suited to analyze these systems. Compared to analytical techniques, agent simulation provides the flexibility to model the complexities and dynamics of real world supply chains without having to perform excessive simplifying assumptions [7]. However, the simulation approach can't guarantee optimality.

2.3 Holonic Agents

MAS has become a natural tool for modeling and simulating complex systems. However, in those systems there usually exist a great number of entities interacting among themselves, and acting at different levels of abstraction. In this context, it seems unlikely that MAS will be able to faithfully represent complex systems without multiple granularities. That's why holonic systems have attracted the attention of researchers [4]. The term holon was coined by Arthur Koestler [5], based on the Greek word holos for whole and on for part. Thus, a holon is a self-similar or fractal structure that consists of several holons as components, and is itself a part of a greater whole. It should meet three conditions: to be stable, to be autonomous and to be able of cooperating. Gerber et al. [3] propose three types of structures for holons, which vary with respect to the autonomy of the members. The moderated group is the intermediary structure, which was chosen for this work due to its greater flexibility. It specifies a holonic organization with two main roles: *head* and *part*. The *head* is a kind of moderator of the holon, represents its shared intentions and negotiates them with agents outside the holon, as well as with those inside the holon. Only the *head* can communicate with the outer world. On the other hand, the *part* is any other member of the holon. Figure 1 outlines the holonic organization of this work.

2.4 Distributed Constraint Optimization Problem (DCOP)

DCOP is a formalism that can model problems distributed due to their nature. These are problems where agents try to find assignments to a set of variables that are subject to constraints. The reason for the distribution of the solving process comes from the assumption that only a subset of the agents has knowledge of each given constraint [10]. Unlike agent-based simulation, this approach allows global optimization. It is assumed that agents maximize their cumulated satisfaction by the chosen solution. This is different from other related formalisms involving self-interested agents, which try to maximize their own utility individually. Thus, the agents can optimize a global function in a distributed fashion communicating only with neighboring agents, and even in a asynchronous way. That framework has proved to be naturally suitable to model different types of complex combinatorial problems, including the oil industry domain [6]. A DCOP can be formalized as a tuple (A, V, D, C, F) [8] :

- $A = a_1, a_2, \ldots, a_n$ is a set of n agents,
- $V = x_1, x_2, \ldots, x_n$ is a set of n variables, each one associated with an agent,
- $D = D_1, D_2, \ldots, D_n$ is a set of finite and discrete domains each one associated with the corresponding variable,
- $C = f_{ij} : D_i \times D_j \rightarrow N$, with $i,\ j = 1..n,\ i \neq j$ is a set of constraints, represented by a cost function f_{ij} for each pair of variables x_i and x_j,
- $F = \sum F_{ij}(d_i, d_j)$, where $x_i \leftarrow d_i, x_j \leftarrow d_j,\ x_i, x_j \in$ V, is the objective function.

Only the agent has knowledge and control over values assigned to variables associated with it. The agents' goal is to choose a valuation for all variables in order to minimize or maximize the objective function F, which is modeled as a set of valued constraints.

3 Problem Description

This work focuses on an oil industry supply chain, which starts at the crude oil extraction, and finishes when its derivative products are delivered to distribution companies, which are considered here as final customers. Thus, all activities that occur before oil extraction, such as exploration and drilling, as well as those that occur after delivery to distribution companies, such as the delivery of products to the gas stations, are out of the scope of this work. The supply of crude oil and its derivatives must be made preferentially by the oil company itself, which may be a single verticalized petroleum enterprise or a set of cooperating companies of the oil business. Henceforth it will be called extended enterprise (EE) the general situation that comprises both cases. If necessary or eligible, the EE can purchase from the spot market (SM), which satisfies any extra demands of crude oil and its derivatives at higher prices. In the same way, SM can buy any exceeding inventories of those items at lower prices. The EE operation area is spread geographically, and this physical space is visualized as a partition of regions, which are in their turn grouped into continents, which finally are gathered into a global area. A region is divided into trading areas or oil extraction areas. A facility, i.e., a refinery or distribution terminal, is responsible for each of the first

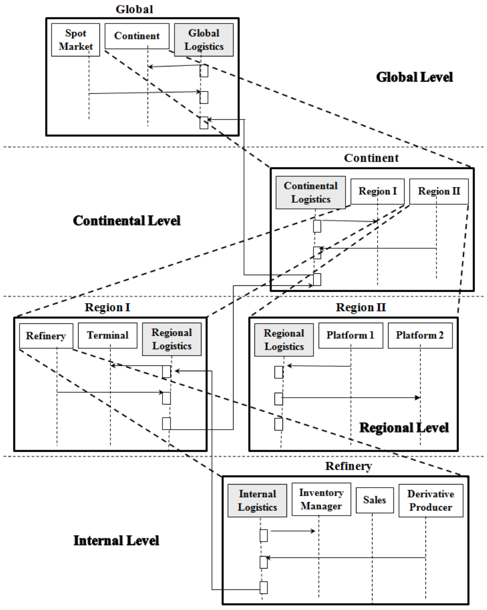

Figure 1. Holonic organization with the *head* agents highlighted

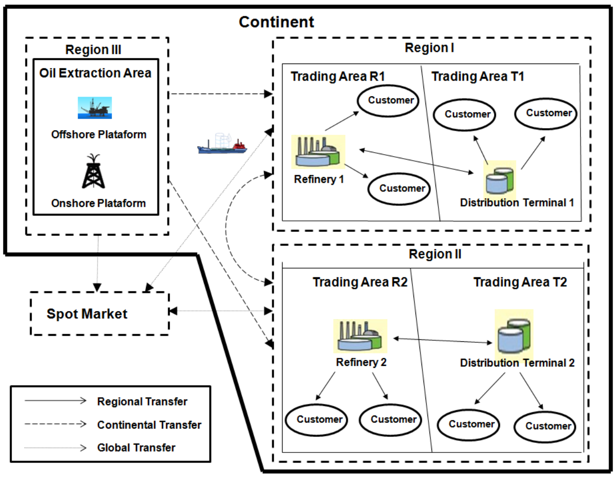

Figure 2. Example of an oil supply chain scenario

ones, which serves specific final customers (distributing companies). On the other hand, each of the latter ones is composed of oil extraction platforms, that yield a certain type of crude oil at a rate that may be considered constant for the time scale of this work.

All the areas are connected by transportation modals, like ships and pipelines. Furthermore, each area owns a specific logistic entity, which is responsible for the transportation planning of crude oil and its derivatives, which, henceforward, will be named just products. Each transportation modal has a set of routes, which connect two entities of the chain (platforms, refineries, terminals, and SM) and has a maximum transportation capacity, which is ignored in this work for the sake of simplicity. If the connected entities belong to a same region, that transport is managed by its regional logistics. Otherwise, the transport is managed by the continental logistics or even the global one, depending on the range of the particular route. Since the facilities are connected through a transportation network, they can cooperate with each other to supply the different trading areas, instead of being restricted to their own ones.

A refinery can produce multiple derivatives, and it does so according to different production plans, which are characterized by processing a definite quantity of a particular type of crude oil and producing a certain quantity of each resulting derivative. In addition, each facility is responsible for the management of its inventories of each product, but platforms can't store the extracted crude oil, which must be drained continuously by ships or pipelines. Thus, each facility should choose and follow a specific inventory policy for each product. Figure 2 illustrates an example of the described oil supply chain.

4 Proposed Model

4.1 Introduction

The model proposes a multi-period time approach. Thus the supply chain system evolves over a given time horizon H, which is divided into periods P_τ,$\tau \in \{1, \ldots, T\}$, which, from now on, will be represented by their index τ. At the beginning of each period τ, decisions are made based on past and future decisions. The sequence of such decisions along H will be called a decision strategy (S), and a decision means the assignment of values to all the decision variables, which are described next.

4.1.1 Decision Variables

A refinery can produce multiple derivatives, and it does so according to different production plans $plan_{r\tau}$, which are chosen from a discrete set generated by the production planner of each refinery r at each period τ. On the other hand, the inventory management of each product p is treated by choosing the inventory $Inv_{fp\tau}$between a minimum and a maximum level for each facility f at each period τ. The first represents the safety inventory, and the latter the physical capacity limit. The inventory policy to be adopted must guarantee that the corresponding inventory level will be equal to $Inv_{fp\tau}$ at the end of the period τ, by replenishing or draining the required product quantity. Thus, the decision variables of the model are :

- $plan_{r\tau}$: production plan adopted by refinery r during period τ;
- $Inv_{fp\tau}$: inventory level of product p (derivative or type of crude oil) in facility f at the end of period τ;

where $\tau \in \{1, \ldots, T\}$, $d \in D$ (set of crude derivatives), $o \in O$(set of types of oil crude), $p \in P = D \cup O$, f is a facility (refinery r or terminal t).

4.1.2 Input Parameters

- $In(r, o, plan_{r\tau})$: quantity of crude oil o processed in refinery r, using production plan $plan_{r\tau}$during period τ;
- $Out(r, d, plan_{r\tau})$: quantity of derivative d produced in refinery r, using production plan $plan_{r\tau}$during period τ;
- $Dm_{fd\tau}$: total expected demand of derivative d in the trading area of facility f during period τ;
- $extRate_{\wp o}$: quantity of crude oil o extracted in platform $\wp$ during a time period;
- $extCost_{\wp o}$: extraction cost of a unit of crude oil o in platform $\wp$;
- $prdCost_{rd}$: production cost of a unit of derivative d in refinery r;
- prc_p: price of a unit of product p in EE's market;

- $SMbuyPrc_p$: price at which SM buys a unit of product p;
- $SMsellPrc_p$: price at which SM sells a unit of product p;
- $InvCost_{fp}(Inv_{fp\tau})$: inventory cost function of inventory level $Inv_{fp\tau}$ for product p in facility f during period τ;
- $RfRate_{Rp}$: freight rate for product p in region R;
- $CfRate_{Cp}$: freight rate for product p between regions in continent C;
- $GfRate_p$: freight rate for product p among continents and SM;

In this work it is proposed a framework based on holonic agents and distributed constraint optimization to model the oil supply chain. The model is divided into two submodels: organization model, and constraint optimization model. The latter gives rise to the distributed constraint optimization model, which is the one actually considered in this work. These models are described in the sections 4.2, 4.3 and 4.4.

4.2 Organization Model

As a result of the features of a holonic system, its organization model can be represented in two dimensions: a *holonic organization*, which is common to all the holonic systems, and an *internal organization*, which is specific to a problem domain [4]. Thus, a same agent can have a role in the holonic organization, and another role in the internal organization. The holonic organization is composed basically of the roles *head* and *part*, whereas, in general, the internal organization comprises more roles, which are associated with physical entities, services and functions of the supply chain. In addition to these specific roles of the internal organization, two generic roles are shared by several of them. The first is the *supplier* role, which refers to any entity that provides products to other entity of the chain. The other is the *client* role, which is played by any entity which needs these products. Figure 3 presents the UML class diagram which represents the roles of the internal organization and the relationships between them. Thus, the *refinery* is modeled as a *terminal* with a *derivative producer*, since both of them own a *sales* and an *inventory manager* area, and an *internal logistics*. The *logistics* is the *head* of the respective holon in all levels of the chain, i.e., the *internal logistics* for the holon *refinery* or *terminal*, the *regional logistics* for the holon *region*, and so on, up to the *global logistics* for the holon *global*. Each *logistics* is responsible for the balance of products between the *suppliers* and the *clients*. The *external logistics*, which represents all the logistics roles, but the internal one (operates inside a facility), is responsible for the transportation planning as well. As to the *production planner* role, it is played inside the refinery by a software or a team of human experts, which support the *derivative producer* role. The *sales* role, in turn, is responsible for the forecast of the total demand for each derivative at the corresponding trading area. Figure 4 shows an UML collaboration diagram, which represents the relationships between the roles in the organization model.

The holonic agent architecture allows a complicated process to be decomposed into smaller processes, which are further decomposed, until each of them can be handled by a single agent. The *header* agent acts as a mediator, which supports communication and control for each level of process decomposition. Although it would be possible a smaller granularity, with agents representing operational units of the refinery, in this work that "descent" comes to an end at the *derivative producer*, which puts up a discrete set of production plans, that are obtained from the *production planner*.

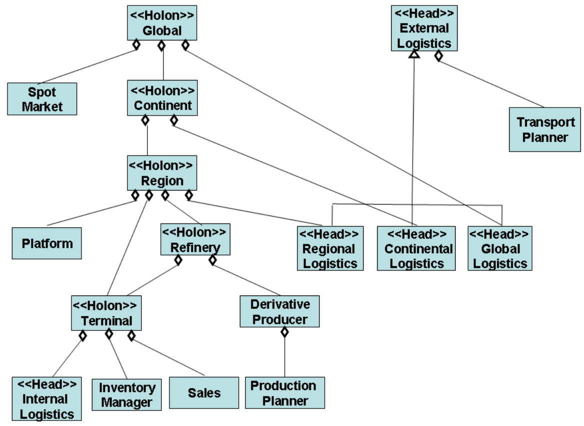

Figure 3. Class diagram of the organization model

4.3 Constraint Optimization Model

A constraint network is a declarative structure, which expresses relations and tolerances among entities. It consists of a number of nodes that are connected by constraints. Multi-agent is one of the approaches that can be used to model and implement constraint networks. Therefore, agent technology and constraint network can be integrated together to support coordination and sharing of information among facilities in supply chains. When the relationships between agents are modeled by constraints, they can be integrated as a network, and global optimization becomes possible. Each agent can be assigned to model a facility and relationships can be defined as constraints between these agents. These relationships pertain to how the products flow from suppliers to clients, and can be represented in quantities of products, in cost or scheduling of deliveries, etc. The environment imposes limitations to the supply chains, which have their significant variables assigned to values within finite domains.As a result, the constraint model considers a finite set of variables, which are associated with a finite domain, and a set of constraints that restrict the values which the variables can simultaneously take.

4.3.1 Constraints

The constraints of the model are expressed in terms of the decision variables and the input parameters. However, to make it easier, the model employs dependent variables, which are defined as follows :

- $\Delta_{\alpha p\tau}$: the difference between output and input quantities of product p with respect to the entity α during period τ;
- $\Delta^+_{\alpha p\tau} = \begin{cases} \Delta_{\alpha p\tau}, & if\ \Delta_{\alpha p\tau} \geq 0 \\ 0, & if\ \Delta_{\alpha p\tau} < 0 \end{cases}$
- $\Delta^-_{\alpha p\tau} = \begin{cases} -\Delta_{\alpha p\tau}, & if\ \Delta_{\alpha p\tau} \leq 0 \\ 0, & if\ \Delta_{\alpha p\tau} > 0 \end{cases}$

Using all the variables and parameters, the constraints are presented for each level of the organizational model.

i. Internal Level

$$\Delta_{rd\tau} = Out(r, d, plan_{r\tau}) - Dm_{rd\tau} + Inv_{rd\tau-1} - Inv_{rd\tau}$$
$$\Delta_{td\tau} = Inv_{td\tau-1} - Inv_{td\tau} - Dm_{td\tau}$$
$$\Delta_{ro\tau} = Inv_{ro\tau-1} - Inv_{ro\tau} - In(r, o, plan_{r\tau})$$
$$\Delta_{\wp o\tau} = extRate_{\wp o}$$

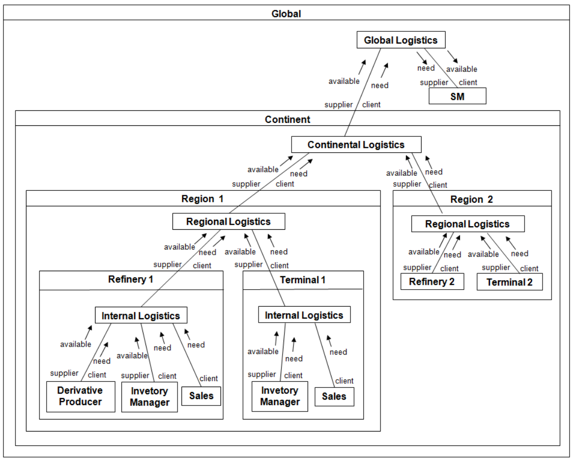

Figure 4. Collaboration diagram of the organization model

ii. Regional Level

$$\Delta_{Rp\tau} = \sum_{f \in R} \Delta_{fp\tau}$$

iii. Continental Level

$$\Delta_{Cp\tau} = \sum_{R \in C} \left(\Delta^{+}_{Rp\tau} - \Delta^{-}_{Rp\tau+1}\right)$$

iv. Global Level

$$\begin{gathered} \Delta_{Gp\tau} = \sum_{C} \left(\Delta^{+}_{Cp\tau} - \Delta^{-}_{Cp\tau+2}\right) \\ \Delta^{+}_{Gp\tau} - \Delta^{-}_{SMp\tau+2} = 0 \\ \Delta^{+}_{SMp\tau} - \Delta^{-}_{Gp\tau+2} = 0 \end{gathered}$$

It is important to point out the relationship between past and future, which appears in the continental and global levels. It comes from the physical time constraints associated with the transport of products between the entities of the chain. In fact, it is assumed in this work that the products take about one time period to be transported between different regions inside a continent (continental level), whereas they take about two time periods to travel between two continents, or from a continent to SM (global level). As to the regional level, it is assumed that two different facilities of a same region are close enough to move their products between each other within a single time period.

Since the time period is limited, i.e.,$\tau \in \{1, \ldots, T\}$, it is necessary to take into account the boundary conditions $\Delta^{-}_{RpT+1} = 0$, $\Delta^{-}_{CpT+1} = \Delta^{-}_{CpT+2} = 0$, $\Delta^{-}_{GpT+1} = \Delta^{-}_{GpT+2} = 0$, $\Delta^{-}_{SMpT+1} = \Delta^{-}_{SMpT+2} = 0$, and $Inv_{fpT-1} = cte$.

4.3.2 Objective Function

The supply chain manager's motivation is to choose a decision strategy $S(plan_{r\tau}, Inv_{fp\tau})$ such that the chosen performance measure is the best possible. In this work, the adopted performance measure is the profit of the entire supply chain during H. However, one of the basic assumptions of the model is that all the customer demands must be supplied. That is always possible due to the flexibility offered by SM, which can buy or sell unbounded quantities of any product. Therefore, the objective is to maximize the total profit with the customer satisfaction automatically guaranteed.

The total profit can be expressed as :

$$\begin{gathered} Profit(S) = Income(S) – Cost(S) \\ Income(S) = COInc(S) + DPInc(S) \\ Cost(S) = COCost(S) + DPCost(S) + \\ + Freight(S) + InvCost(S) \end{gathered} \tag{1}$$

$COInc$ is the income obtained by selling the surplus crude oil to SM; $DPInc$ comes from the sale of all the derivative products, internally and to SM as well; $COCost$ is the cost resulting from crude extraction or its purchase from SM in order to feed the refineries; $DPCost$ is the total cost to produce the derivatives in the refineries, and the prices paid to SM when a purchase is necessary to supply the whole demand of customers; $Freight$ is the total freight of the transportation of crude and derivatives, and is obtained by the sum of the freights of transfer of products inside each region($Rfrt_{Rp\tau}$), between different regions in a same continent ($Cfrt_{Cp\tau}$), and among continents and SM ($Gfrt_{p\tau}$); finally, $InvCost$ is the total inventory cost to store derivatives and crudes during H.

$$\begin{gathered} COInc(S) = \sum_{o\tau} SMbuyPrc_o \cdot \Delta^{+}_{Go\tau} \\ DPInc(S) = \sum_{fd\tau} prc_d \cdot Dm_{fd\tau} + \sum_{d\tau} SMbuyPrc_d \cdot \Delta^{+}_{Gd\tau} \end{gathered} \tag{2}$$

$$\begin{gathered} COCost(S) = \sum_{o\tau} SMsellPrc_o \cdot \Delta^{-}_{Go\tau} + \sum_{\wp o\tau} extCost_{\wp o} \cdot \Delta_{To\tau} \\ DPCost(S) = \sum_{rd\tau} prdCost_{rd.} \cdot Out(r, d, plan_{r\tau}) + \\ + \sum_{d\tau} SMsellPrc_d \cdot \Delta^{-}_{Gd\tau} \\ InvCost(S) = \sum_{fp\tau} InvCost_{fp}(Inv_{fp\tau}) \end{gathered} \tag{3}$$

$$\begin{gathered} Freight(S) = \sum_{Rp\tau} Rfrt_{Rp\tau} + \sum_{Cp\tau} Cfrt_{Cp\tau} + \sum_{p\tau} Gfrt_{p\tau} \\ Rfrt_{Rp\tau} = \begin{cases} \sum_{f \in R} \Delta^{+}_{fp\tau} \cdot RfRate_{Rp}, & if\ \Delta_{Rp\tau} < 0 \\ \sum_{f \in R} \Delta^{-}_{fp\tau} \cdot RfRate_{Rp}, & if\ \Delta_{Rp\tau} \geq 0 \end{cases} \\ Cfrt_{Cp\tau} = \begin{cases} \sum_{R \in C} \Delta^{+}_{Rp\tau} \cdot CfRate_{Cp}, & if\ \Delta_{Cp\tau} < 0 \\ \sum_{R \in C} \Delta^{-}_{Rp\tau} \cdot CfRate_{Cp}, & if\ \Delta_{Cp\tau} \geq 0 \end{cases} \\ Gfrt_{p\tau} = \begin{cases} \left(|\Delta_{Gp\tau}| + \sum_{C} \Delta^{+}_{Cp\tau}\right) \cdot GfRate_p, & if\ \Delta_{Gp\tau} < 0 \\ \left(|\Delta_{Gp\tau}| + \sum_{C} \Delta^{-}_{Cp\tau}\right) \cdot GfRate_p, & if\ \Delta_{Gp\tau} \geq 0 \end{cases} \end{gathered} \tag{4}$$

4.4 Distributed Constraint Optimization Model

From the previous constraint model, it is possible to derive a distributed constraint model, which employs the same parameters, decision and dependent variables of the first one. Basically, whatever the role in the organization model, but the *logistic* ones, one agent is created for each tuple (p,τ). On the other hand, a single agent exists per *logistic* entity in the case of *logistic* roles. Since the *logistic* agents of all the levels have also the *head* role, they are responsible for the computation of the dependent variables, which are updated according to the decision variables assignments and sent upward from a *logistic* agent to the other located in the upper level. Furthermore, the appropriate match between the correct time periods while balancing availabilities of *suppliers* and needs of *clients* in the continental and global levels is also a responsibility of the corresponding *logistic* agent. The agents of the *derivative producer* role manage the decision variables $plan_{r\tau}$, whereas the agents of the *inventory manager* role take care of the decision variables $Inv_{fp\tau}$.

The objective function represents the total profit, and therefore is to be maximized. It is written as $F = \sum F_{L:\alpha}$, where the valued constraint functions $F_{L:\alpha}$ are defined as relationships between two agents (neighbors). In the focused holonic model, one agent of the couple has always one of the *logistic* roles (L), whereas the other can play any of the other roles (α). Each of these functions is presented next, along with the pair of neighbor agents, and the variables exchanged by them, as well as the parameters, since these latter can change dynamically according to the environment. In case of a holon, it is followed by its *head* agent (symbol $\equiv$), which represents the entire holon in the communication. All the variables act directly on the objective function, whereas some parameters do so and others not ($F_{L:\alpha} = 0$).

4.4.1 Constraints

i. Internal Level

$\textbf{\textit{Sales}}_{fd\tau} \xrightarrow{Dm_{fd\tau}} \textbf{\textit{Internal Logistics}}_f$
$F_{L_f:S_{fd\tau}} = prc_d \cdot Dm_{fd\tau}$

$\textbf{\textit{Inventory Manager}}_{fp\tau} \xrightarrow{Inv_{fp\tau}} \textbf{\textit{Internal Logistics}}_f$
$F_{L_f:M_{fp\tau}} = -InvCost_{fp}(Inv_{fp\tau})$

$\textbf{\textit{Derivative Producer}}_{ro\tau} \xrightarrow{In(r,o,plan_{r\tau})} \textbf{\textit{Internal Logistics}}_r$
$F_{L_r:D_{ro\tau}} = 0$

$\textbf{\textit{Derivative Producer}}_{rd\tau} \xrightarrow{Out(r,d,plan_{r\tau})} \textbf{\textit{Internal Logistics}}_r$
$F_{L_r:D_{rd\tau}} = -prdCost_{rd} \cdot Out(r, d, plan_{r\tau})$

ii. Regional Level

$\textbf{\textit{Facility}}_{fp\tau} \equiv \textbf{\textit{Internal Logistics}}_f \xrightarrow{\Delta_{fp\tau}} \textbf{\textit{Regional Logistics}}_R$
$F_{L_R:F_{fp\tau}} = -RfRate_{Rp} \cdot \Delta^+_{fp\tau}$

$\textbf{\textit{Platform}}_{\wp o\tau} \xrightarrow{\Delta_{\wp o\tau}} \textbf{\textit{Regional Logistics}}_R$
$F_{L_R:P_{\wp o\tau}} = -\left(RfRate_{Ro} + extCost_{\wp o}\right) \cdot \Delta^+_{\wp o\tau}$

iii. Continental Level

$\textbf{\textit{Region}}_{Rp\tau} \equiv \textbf{\textit{Regional Logistics}}_R \xrightarrow{\Delta_{Rp\tau}} \textbf{\textit{Continental Logistics}}_C$
$F_{L_C:R_{Rp\tau}} = RfRate_{Rp} \cdot \Delta_{Rp\tau} - CfRate_{Cp} \cdot \Delta^+_{Rp\tau}$

iv. Global Level

$\textbf{\textit{Continent}}_{Cp\tau} \equiv \textbf{\textit{Continental Logistics}}_C \xrightarrow{\Delta_{Cp\tau}} \textbf{\textit{Global Logistics}}$
$F_{L_G:C_{Cp\tau}} = CfRate_{Cp} \cdot \Delta_{Cp\tau} - GfRate_p \cdot \Delta^+_{Cp\tau}$

$\textbf{\textit{SM}}_{p\tau} \xrightarrow{SMsellPrc_p, SMbuyPrc_p} \textbf{\textit{Global Logistics}}$

$$F_{L_G:SM_{p\tau}} = -GfRate_p \cdot \Delta^+_{SMp\tau} - SMsellPrc_p \cdot \Delta^+_{SMp\tau} + \\ + SMbuyPrc_p \cdot \Delta^-_{SMp\tau}$$

5 Conclusion

In this paper, we have developed a theoretical model that combines a constraint network approach and a holonic multi-agent approach to support coordination and management of a typical oil industry supply chain. Agents capture the distributed behavior of the supply chain, and the holonic approach makes it possible to represent its intrinsic recursive nature. On the other hand, the constraint network model allows a tight integration of the chain entities, which are spread in space and time, and allows optimization. In a usual simulation approach, each decision is based only on past decisions, but this model integrates both the past and the future, and allows an actual optimization.

The proposed model is divided into an organization and a constraint model. The first consists of a holonic organization of the kind moderated group, and an internal organization suited to the oil supply chain domain. The constraint model is refined to a distributed constraint model, which is the one to be considered.

In a future work the model will be extended to include transport constraints and the transport planning by the distribution of product transfers among the available routes. The responsibility for these tasks will be assigned to the corresponding *logistic* agent. The inclusion of such constraints will restrict the search space to be explored, aiming at the optimization. The process of negotiation with the *production planner* will also be detailed within the *derivative producer* of each refinery, aiming at the choice of the eligible best production plans for the decision variable domain. Finally, it will be developed a prototype based on a case study, as a proof-of-concept to validate the proposed model, which will be compared with actual historical data.

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