

# **A Decentralized Multi-Issue Approach for Automated Supply Chain Formation**

**PhD Thesis Summary**

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Cluj-Napoca, 2018

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### **Bibliography**

**Keywords:** Supply Chain Formation, Supply Chain Contracts, Intelligent Agents, Utility Functions, Automation, Cluster Graph, Variable Elimination, Belief Propagation, Max-Sum, Maximum Expected Utility

## Publications

The material contained in this thesis was disseminated and contribute to the following publications:

1. COVACI Florina Livia, *Optimizing Service Level Agreements in Peer-to-Peer Supply Chain Model for Complex Projects Management*, Editors: Silaghi G., Buchmann R., Boja C., Informatics in Economy. Lecture Notes in Business Information Processing, vol 273. pages: 23-37, Springer, 2017, ISBN/ISSN: 978-3-319-73458-3.

2. COVACI Florina Livia, *Agent-Based Simulation for Peer to Peer Supply Chain Formation*, 30th European Simulation and Modelling Conference, Editors: Jose Evora-Gomez and Jose Juan Hernandez-Cabrera, EUROSIS, pages: 429-434, 2016, ISBN/ISSN: 978-90-77381-95-3.

3. COVACI Florina Livia, Bologa Cristian-Sorin, Silaghi Gheorghe-Cosmin, *Expected Utility and Risk Management in Complex Projects*, Information Systems Development: Advances in Methods Tools and Management (ISD2017 Proceedings), 26th International Conference on Information Systems Development (ISD2017 Cyprus), AIS, Editor: N. Raspopoulos M. Barry M. Lang H. Linger and C. Schneider, Pages: 1 - 9, 2017, ISBN/ISSN: 978-9963-2288-3-6.

4. COVACI Florina Livia, *A Multi-Agent Negotiation Support System for Supply Chain Formation*, Hohenheim Discussion Papers In Business Economics and Social Sciences, 17th International Conference on Group Decision and Negotiation, Hohenheim University, Editor: Mareike Schoop and D. Marc Kilgour, Pages: 229 - 238, 2017, ISBN/ISSN: 2364-2084.

5. COVACI Florina Livia, *Industry 4.0-Towards Automated Supply Chain Formation*, Hohenheim Discussion Papers In Business Economics and Social Sciences, Doctoral Consortium of 17th International Conference on Group Decision and Negotiation, Hohenheim University, Editor: Mareike Schoop and D. Marc Kilgour, Pages: 27-36, 2017, ISBN/ISSN: 2364-2084.

6. COVACI Florina Livia, *Modelling and Simulation for Decentralized Supply Chain Formation*, Proceedings of the 31st European Simulation and Modelling Conference, 31st European Simulation and Modelling Conference, Editor: Paulo J.S.Goncalves, EUROSIS, Pages: 185-192, 2017, ISBN/ISSN: 978-9492859-00-6.

# Chapter 1

## Introduction

In the vision of Industry 4.0, most processes in the enterprises will become more digitized. Algorithms will enable machines to make autonomous decisions in the digitized supply chain of the future.

The members in a Supply Chain (SC) are dependent on each other on information and resources, this increased dependency being owed to globalization, outsourcing and fast advances in information technologies. The increased dependency is bringing along with benefits, a certain amount of risk and uncertainty also. In order to address these challenges, the SC participants must coordinate with each other. The appropriate coordination mechanisms need to be identified in order to address the uncertainties in supply chain and for the supply chain coordination to be achieved (Arshinder et al. 2008).

Supply chain participants coordinate by making use of contracts, this providing better risk management and improved management of the relationship between suppliers and consumers. Within the contracts, the parameters that need to be fulfilled in a supplier-consumer partnership are specified (Arshinder et al. 2008). The benefits for using supply chain contracts are: increased of the overall supply chain performance, reduced costs for stock management and risk sharing among the supply chain participants (Tsay 1999).

In the following we provide the contributions of this thesis in order to overcome several limitations of existing SCF literature.

Based on the literature review for automated SCF that we have performed in Chapter 3, we have developed a theoretical framework using the existing approaches for SCF. The theoretical framework that we have development has three dimensions: the type of approach regarding an existing central authority, techniques employed for modeling communication and whether the approaches are addressing or not multiple units.

Analyzing the results obtained in the literature review process of chapter 3, we assessed that the following research questions are worth to be considered:

1. As in real world scenarios the SCF problem is a complex one and deals with multiple contract issues, is it possible to find a mechanism for SCF that involves multiple parameters?
2. Related to the first question, a second question arises: If the SCF mechanism would involve multiple parameters, how can be assessed the optimal supply chain?
3. What if there is need to deal with complementary products in the SCF process?
4. Is there a way to incorporate risk in the SCF mechanism?

Hence, the present thesis enlarges the state-of-the-art with respect to the topic of automated supply chain formation with the following contributions:

1. Provides means for incorporating multiple contract parameters like: cost, quality, delivery constraints, etc. in the negotiation of the contract terms. Moreover, the proposed mechanism can incorporate in the utility functions even subjective parameters that are not shared by other entities. These subjective parameters are not involved in the contracts but influence the decision of a consumer (e.g. color). As they are not always part of a contract in a trading relationship, they can be removed from the agreed contract with the variable elimination mechanism described in the proposed MCP-BP algorithm in Chapter 5.
2. Makes use of utility functions as a way to express preferences over the states of variables and to assess the optimal supply chain. Hence, the SCF problem gets closer to real world scenarios.
3. Provides means for dealing with complementary products as there are frequent situations when intermediate suppliers require complementary products in order to deliver a more complex product or sub-assembly at upper levels in the supply chain.
4. Provides a mechanism to incorporate risk in the assessment of the optimal supply chain. Moreover in Chapter 6, we use two case studies, for two different economic fields, in order to validate the proposed mechanism.



The continuing of this dissertation is organized as follows:

In Chapter 2, we describe the problem statement providing a general background for the current thesis and we discuss about contracts in supply chains.

In Chapter 3, we provide a literature review that was the base for building a theoretical framework with three perspectives regarding SCF. This literature review was needed for understanding the concepts and identifying the shortcomings in the existing literature.

In Chapter 4, we provide the mathematical background for the proposed approach regarding SCF. We introduce the notion of factors and their roles in graphical models. Next, we describe the variable elimination algorithm and describe the cluster graphs and max-sum algorithm. Last we emphasize the idea of maximum expected utility and influence diagram.

In Chapter 5, we provide the formalization of our approach for the SCF problem in which each participant is assigned to a cluster in a cluster graph. The participants have a utility function and they exchange messages regarding their preferences over a cluster graph using max-sum algorithm. Moreover, we provide a method for incorporating risk in the decision making by the means of utility diagram and maximum expected utility. Finally we give an evaluation of our approach and empirical results on the types of networks used by previous authors in the existing related work for SCF.

Furthermore, in Chapter 6 we provide two business case studies in two completely different industries (Information Systems Development and Petroleum Industry) in order to validate our approach and give a better understanding, closer to real world scenarios.

Finally, in Chapter 7, we outline several conclusions and we describe directions for future research.

## Chapter 2

# Problem statement

The current thesis considers the problem of supply chain formation as a form of coordinated commercial interaction. The considered supply chain scenario represents a network of production and exchange relationships that spans multiple levels of production or task decomposition. This supply chain model is typically used in manufacturing industries that produce complex goods (planes, cars, petrochemical industry etc.) but any service or contracting relationship that spans multiple levels can be mapped to this supply chain scenario.

The agents are characterized in terms of their capabilities to perform tasks, and their interests in having tasks accomplished. A central feature in the considered scenario is hierarchical task decomposition: in order to perform a particular task, an agent may need to achieve some sub-tasks, which may be delegated to other agents. These tasks are also composed of sub-tasks, which are further delegated to other agents. As a consequence, a supply chain is formed, by decomposing the task realization at each level to the agents that are responsible for each sub-task. Constraints on the task assignment arise from the underlying suppliers network as exemplified in Figure 2.

The final product owner  $X_1$  at the root of the supply chain can choose among  $X_2$ ,  $X_3$ ,  $X_4$  and  $X_8$  sub-assembly suppliers. The length of the four possible supply chains is different because there may be first tier suppliers that are able to produce the sub assembly without further task decomposition. At lower levels a certain sub-assembly supplier or a certain part supplier has the option of choosing among multiple possible descendant suppliers. For example  $X_3$  may choose  $X_6$  or  $X_{11}$  as his fabricated part supplier and  $X_5$  may choose between  $X_7$  and  $X_{12}$  as raw material suppliers.

Given the above-described environment, our research aims to find a mechanism for linking end-consumer requirements to underlying suppliers to conjointly guarantee end-to-

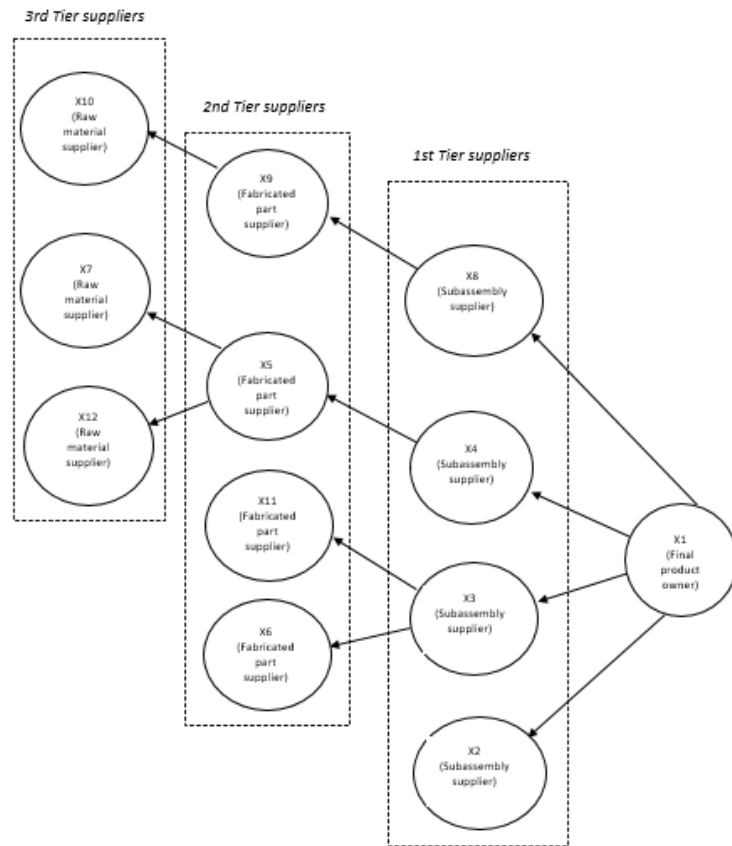


Figure 2.1: Example of supply chain with hierarchical task decomposition (Covaci 2017)

end agreed contract parameters.

The following specific relevant research challenges subsequent to the overall research aim exposed above were identified:

1. We will model the task assignment between a consumer and a provider by a contract, which can involve many issues like the price or the cost, quantity delivered, specific constraints for various quality issues, the risk of violating the contract - tackled with penalty clauses, etc. Entities part of the supply chain will need to agree on these contract parameters, as they will bring them a variable utility, according to their specific preferences over the values of the parameters. Thus, a first research challenge is how to model interactions within the supply chain through contracts with multiple parameters, given that agents act independently and they are selfish - ie. their utility functions do not depend each on another and all of them wish to maximize their perceived utility after the contract realization.

2. An inner agent within the supply chain can be in the same time both a consumer and a producer. Thus, she will pursue a dual role in the local interactions that she is part of, complicating the SCF. Within these interactions, agents will need to confirm to their suppliers that the issues under discussion could be accommodated and paid, and respectively to their consumers that she can deliver the contract. Thus, a challenge of our research will be to model the information flow within the supply chain, such that a solution will be obtained and that solution has some overall beneficial properties.

Key to our approach will be the fact that we will see the interaction between adjacent agents as an agreement over contracts with multiple parameters. Therefore, below we will shortly discuss the impact of contracts upon the decentralized supply chain performance.

Due to globalization process and outsourcing practices, the decentralized scenarios where multiple decision makers own partial information and have various preferences, are widespread nowadays. The measurement of decentralized supply chains performance can be performed by using coordination as an assessment criterion. The coordination can be achieved by means of agreed contracts between entities in the supply chain.

In a decentralized system, due to the incompatibility of the incentives of agents, the decisions that are optimal for the agents may be sub-optimal for the supply chain as a whole. The incompatibility of incentives in decentralized supply chains resides in the fundamental characteristic of the agents: rationality. This rationality of individuals involves that each agent is seeking at maximizing its own utility and each agent is being able to estimate her optimal decisions given the available information, which leads to the maximization of her utility. As a consequence, the agents will assume the supply chain optimal decisions only if they understand that those decisions are also optimal for themselves.

In order to get to a supply chain allocation with participants agents that are satisfied and are accepting the allocation, within the coordinating contracts, the optimum decisions of an agent must be the same as the optimum decisions for the overall SC. This can be achieved either by satisfying the minimum acceptable utilities for all agents or dividing the resulted payoffs fairly among all agents (Behzad & Wiesaw 2010).

Some of the most important clauses, as viewed by the literature, following the enumeration of (Hohn 2010) are: Specification of decision rights, Pricing, Minimum purchase commitment, Quantity flexibility, Buy-back or returns policies, Allocation rules, Lead time, Quality, Horizon length, Periodicity of ordering, Information sharing

The premise of this thesis is that the interactions between buyers and suppliers at all levels in the supply chain are governed by formal contracts. Usually these contracts have to capture the three kind of flows that are involved in the interactions between the participants in the supply chain: financial, information and material flows.

Within the agreeing process over a contract parameters, each agent will take decisions which are influenced by the history of information that arrive to that agent. Thus, we will approach the decision making situation, based on principles from economics (i.e. utility theory) and we will use the probabilistic graphical models presented in chapter 4 to encode and analyze the local decision making process.

## Chapter 3

# State of the art regarding automated Supply Chain Formation

Based on a structured literature review, in this chapter we develop a theoretical framework that will be helpful in understanding the supply chain formation complexity from multiple perspectives. This analysis will constitute the foundation for further identifying the issues and gaps in the current research literature. This systematic review includes high-rated scientific conferences and journals. The articles considered have been identified by searching keywords, afterwards being confirmed to be relevant for our literature review based on the title, abstract and content. Furthermore, the selection of the papers has been made based on the addressed issue and according to their content, with focus on: (i) the type of approach regarding an existing central authority, (ii) mechanisms employed for modeling information exchanges between the SC participants and (iii) whether they are addressing or not multiple products or bundles in the process of supply chain formation.

The purpose of this chapter is to provide an understanding of the connection of multiple existing approaches and concepts regarding the supply chain formation and identify gaps and issues in the research literature. In order to accomplish this, a two-step approach was performed.

At the first step, a literature review was conducted for creating the theoretical framework in figure 3.1. This framework provides an overview over the most discussed models and technologies inside the relevant works and studies in the literature and classifies them according to the identified key approaches and concepts related to supply chain formation. As shown in the framework, the approaches and concepts can be summarized into three

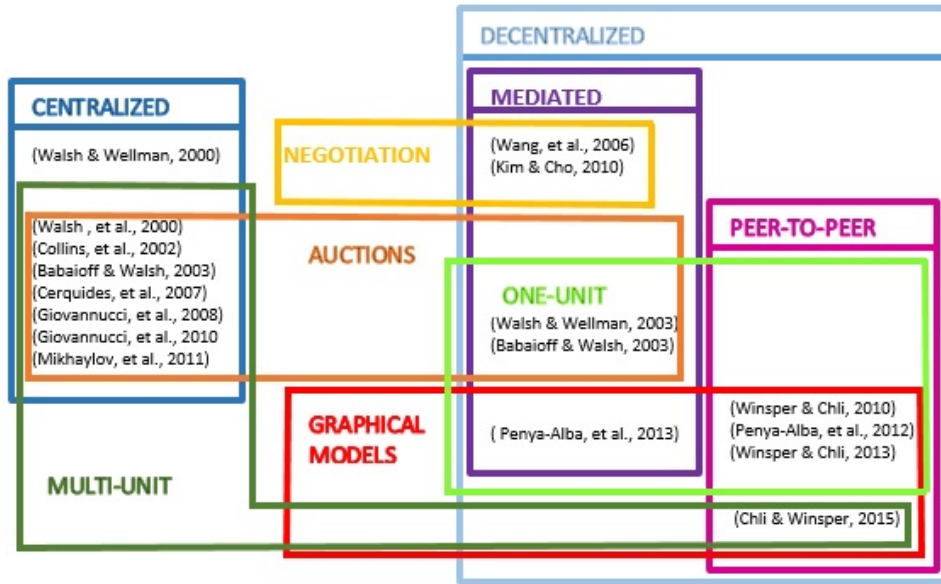


Figure 3.1: Theoretical Framework for Supply Chain Formation

perspectives according to the characteristic features:

1. Approaches used regarding the existence of a central authority,
2. Mechanisms devised for exchanging information between the participants in the supply chain,
3. Usage of multi-unit dimension or bundles for the traded goods.

Second, all the approaches were evaluated to understand and identify gaps and issues in the literature and find future research directions for enabling the digitization within the supply chain formation.

In the following we will point to some drawbacks identified in the above-studied literature. The main scientific contribution of our thesis will be to address these limitations and come with an alternative solution.

- The number of the contract parameters

The existing approaches analyzed in the previous section are considering only the price as the main contract parameter, besides the number of units to be agreed between potential suppliers and consumers. In Industry 4.0 scenarios, the SCF problem is a complex one and deals with multiple issues of the contracts. Involved entities in the

supply chain are negotiating on parameters like quality parameters, delivery time, delay penalties, price etc. We will assume that each participant will assess the value of a contract using utilities.

- Optimality of the resulting supply chain

The assessment of SC obtained by using the approaches presented above is done using only a profit maximization function of the end-consumer entity in supply chain. However, within the context of Industry 4.0, the performance of supply chains is measured throughout a coordination criterion. The term coordination considers environments where exists a single decision maker that has the entire information from various decision makers and is able to optimize the network. However, in environments with multiple decision makers that may have various incentives and information, coordination may face difficulties. Decision makers have an aversity for sharing information regarding the cost and demand, that may end up with sub-optimal supply chain performance. Each decision maker is interested in a set of parameters, hence he has the goal to optimize a individual target function. However the local optimal values don't have to be the same as the global optima for the entire supply chain.

- Risk

An issue that arises from the complexity of Industry 4.0 is the increased risks. For example, there might exist a penalty for every day of delay in delivering the product for the principal contractor in his contract with the main client. He will need to decide which supplier to chose for a critical raw material/assembly. It is often a difficult decision on whether using the higher-priced supplier, even it is know that one is reliable or a lower-priced supplier that also is promising that he will successful deliver, although there is a doubt that he cannot rely on that. There is need for taking into consideration if there are any advantages for using the higher-priced supplier by taking into consideration the risk associated with suppliers. The risk also arises from uncertainties regarding the market conditions. There are markets with high volatility regarding price evolution even in short periods of time. The volatility of prices has an influence for the demand of a certain product, hence when making decision on which suppliers to chose, an participant in the supply chain has to consider the unpredictable evolution of the market they are acting in.



## Chapter 4

# Probabilistic Graphical Models

This chapter presents the theoretical foundation regarding the probabilistic graphical models. We will use the concepts defined here and the main algorithms that allows transforming the graphical models and pursuing inference on their basis in chapter 5. Probabilistic graphical models allow the encoding of the SCF problem within our MPC-BP approach and helps resolving the main issues we identified in chapter 2: dealing with multiple contracts parameters and complementary goods.

1. Graphical models The nodes in a probabilistic graphical model represent random variables or groups of random variables, while the links indicate probabilistic relationships between these variables. The result is a graph that expresses the manner in which it can be decomposed into a product of factors, the joint distribution over all random variables, each factor depending only on a subset of the variables.

Two sorts of probabilistic graphical models exist:

- (i) Bayesian networks, which are directed graphical models and contain directed links
- (ii) Markov random fields, which are undirected graphical models, in which the links do not have a directional significance, hence they don't carry arrows.

Graphical models are centered around the idea of factorization. As indicated by Wainwright & Jordan (2008), such a model encodes a series of probability distribution functions which factorize according to a certain configuration of the graph.

Even though many works emphasize on conditional probabilities encoded in graphical models, Shafer & Shenoy (1990) show that fundamental to local computation - which is of our interest, is a factorization and one should not see this factorization as being mandatory related to conditional probabilities. The local computation can be applied

to arrays of values in general, not only to random variables probability distributions. Thus, it gives a larger generality for the graphical models, having a practical importance and also it permits interpreting the results in terms different from probabilities, because it allows the researcher to focus solely on the computational aspects of the problem.

The factor graph includes two types of nodes: variable nodes - usually depicted as circles and function nodes - usually depicted as squares. Each function is connected to the variables it depends on by undirected links.

Factor graphs are widely used for the graphical representation of factored functions, which can be written as a sum of their components. It precisely depicts the relations between the variables through the functions nodes.

2. Variable Elimination In this section we present the variable elimination algorithm, as a way of dealing with the factors present on a graphical model. Using the factor-based perspective, the variable elimination algorithm can be generally defined such that it can be applied to both Bayesian and Markov networks.

When performing computation of the probability of a subset of variables, the key operation which is performed is the marginalization the variables of a distribution. Computing the marginal distribution over a subset of  $X$  could be viewed as an operation on a factor.

The main idea of the variable elimination algorithm is that the variables are summed out one at each step. When any variable is summed out, all the factors that mention that variable are multiplied, generating a product factor. Then the variable from this combined factor is summed out, generating a new factor that represents the input for the set of factors to be dealt with.

### 3. Cluster Graph

The cluster graph, represents a data structure suitable for the factor-manipulation process in a graphical way. For each subset of variables in the graph we will associate a node in the cluster graph. Undirected edges will connect the nodes in the cluster graph who have a non-empty intersection of the variables within their scope(Koller & Friedman 2009).

#### 4. Clique Trees

If the cluster graph comes out of the execution of the variable elimination algorithm, it is guaranteed not to have cycles and thus it is certainly a tree.

Variable elimination algorithm implies a flow of messages between the participants (i.e. the clusters). Thus, the resulting cluster graph is a directed one, regardless the fact that the input graphical model is directed or not. Within the variable elimination algorithm a directed tree is induced, because all the messages are sent towards a sole cluster, which stands for the final computed probability distribution. This cluster is called the root of the directed tree. Using standard conventions in computer science, it is assumed that the root of the tree is "up", the leaves are "down", therefore, messages are flowing upward to the root of the tree.

The cluster tree induced by variable elimination algorithm satisfies a fundamental constraint: the running intersection property, meaning that all factors hold at least some variable, from the very beginning existence of the factors, until they are summed out.

#### 5. Max-sum Algorithm

In order to apply the graphical models to decision problems, one frequently used algorithm is max-sum. Decision problems are often regarded as optimization ones, as the decision maker should select an alternative from multiple possibilities, optimizing some decision criteria and staying within some externally imposed restrictions. Here, we will shortly present the max-sum algorithm, as SCF literature uses it for decision making.

As indicated by (Bishop 2006), max-sum algorithm could be applied to optimization problems. Roughly speaking, it translates the problem into a factor graph and uses a message passing mechanism in order to find approximate solutions. To apply max-sum algorithm to an optimization problem, the requirement is that the function to optimize can be decomposed additively. Thus, the algorithm evolves in three steps:

- (a) local graph terms are build for each individual component of the function under optimization. These terms are linked in a graph
- (b) edges of the graph carry messages that update the local terms variables, in an iteratively manner

(c) final states of the variables are determined

The key of the max-sum algorithm is the way to compute the values that will be exchanged in each iteration. This is the specific part of each application of max-sum to a particular problem, and also, how max-sum can be mixed with the probabilistic graphical models inference.

## 6. Decision making in the lights of probabilistic graphical models

First we start by introducing the utility theory as it the key foundation for maximum expected utility decision making. Next, we will describe the maximum expected utility of an agent and will map it to graphical models, according with (Koller & Friedman 2009).

### (i) The utility theory

(Koller & Friedman 2009) shows how to model the decision making process with the help of graphical models. One key assumption is that agents are rational and use the utility theory as a ground for taking actions. In decision-making situations, agents needs to choose between a set of possible actions. Each action leads to one of several outcomes, for each of these possible outcomes the agent having different preferences. In the most simple case, the outcome of each action is known precisely. In this case, the agent will select that action that will get her to the most preferred outcome. But how to decide about the preferred outcome? In similar decision making situations, different agents could have a different preferred outcome, based on their internal structure. Thus numerical values, named utilities, should be assigned for the possible outcomes, permitting the agent to perform a rigorous decision making process.

As noted by Fishburn (1968), utility theory is inquisitive in the preferences of the people, letting those preferences to be expressed as numbers - as we wish to use in our decision making process. To arrive the number-based encoding of the preferences, the relations of preference over issues of interest are defined.

### (ii) Maximum expected utility

Maximum Expected Utility(MEU) provides a general framework allowing agents to make decisions by assigning a numerical utility for each different outcome. The utility function of an agent describes her overall preferences, that can be dependent not only

on monetary measures, but also on all other relevant aspects. For an agent taking part of the supply chain, each outcome  $o$  of the interaction within the supply chain will be evaluated with a numerical value  $U(o)$ , expressing how happy is the agent with that given outcome  $o$ . It is important to note that utilities are not just ordinal values, denoting the agents preferences between the outcomes, but they are numbers, thus enabling the agent to fine-grain express the preference over an alternative, against another one. Probabilistically speaking, using numbers as output of the utility functions permits one to aggregate the preferences of the agents over multiple parameters and develop numerical evaluations for possible outcomes, given an enlarged set of parameters or criteria.

Rational agents will maximize their expected utility in each decision making situation  $D$ , i.e. will select the action that gives them the output with the perceived maximum utility.

A utility function maps from possible outcomes to numerical values. These outcomes can vary along multiple dimensions. Most of the time, monetary gain substitutes the utility function. But economics (Kreps 1990) recommends to incorporate in the utility function all attributes of interest for the decision making situation. Broader utility functions let economics to justify as rational the decisions taken by agents where the monetary gain is not maximized.

At the basis of our study, we will consider the basic utility function over a single attribute of interest and the overall utility of an agent, over all parameters, to be additively decomposed in simple utility functions.

When focusing on outcomes involving only a single attribute, the utility function can be written as a table when there are discrete outcomes, or as a curve when the outcomes are continuous-valued. In practice, however, outcomes often involve multiple attributes. An utility function should provide numerical values for outcomes originating from various combinations between the different attributes and the agent preferences over them.

In such scenarios the utility function should map all the possible combination of the values for the interest parameters to single numbers.

Therefore, the utility function can be viewed in terms of a graphical model (Koller & Friedman 2009). Specifically, a Markov network undirected graph could be drawn for a utility function. The independence relations in the utility function are expressed by the separation properties of the graph. If the utility function can be decomposed additively, this can be done along the maximal cliques of the graph.

## 7. Influence Diagram

Given the decision making setting presented in the previous subsection, where agents take actions based on the maximum expected utility principle, Koller & Friedman (2009) shows how this setting can be modeled with the usage of graphical models, more specifically within the framework of the Bayesian networks. As SCF represents a broad decision making situation and we will use the graphical models in order to describe our scientific contribution in chapter 5, here we will describe the influence diagrams.

The influence diagram concept enlarges the framework of the Bayesian networks. According with its definition, the decision making situation contains probabilistic outcomes and utility functions thus, it is worth to represent the decision making situation using this set of variables. Some of the variables are chance variables that take nature controlled values according to some probabilistic model. Others variables are under the control of the agents, reflecting their choices. Finally, there are also numerically variables that encode the utility of the agent.

Therefore, a directed graph could be employed to graphically depict the decision making situations. This graph will contain three sorts of nodes, related to the types of variables enumerated above. We will draw ovals for random variables, rectangles for decision variables and diamonds for utilities. The graph will contains no cycles, because we impose that utility nodes have no children (Koller & Friedman 2009).

## Chapter 5

# Decentralized Supply Chain Formation with Multiple Contract Parameters (MCP-BP)

### 1. MCP-BP Algorithm

We formally describe the supply chain formation problem in terms of a directed, acyclic graph  $(X, E)$  where  $X = \{X_1, X_2, \dots, X_n\}$  denote set of participants in the supply chain represented by agents and a set of edges  $E$  connecting agents that might buy or sell each from another.

Let  $I = \{I_1, I_2, \dots, I_n\}$  be the set of parameters that the participants in the supply chain formation process need to agree on. The participants share multiple contract parameters and SCF finishes with a contract that is composed of the actual values of the parameters that they have agreed on.

We denote by  $U(v)$  the utility that a participant gets by obtaining the actual value  $v = (v_{I_1}, v_{I_2}, \dots, v_{I_k})$  of the contract parameters. The agents don't know each other utility functions, they are aware only of the values of the discrete states variables they share and their own utility values obtained for each combination of the values of the shared variables. During the supply chain formation process, each agent wants to maximize its utility function under the constraints from the underlying suppliers, so that the utility obtained by an individual agent,  $U(v)$  is dependent on its own utility function and the states of the agents in the lower levels of the supply chain. The number of variables within the utility function may be different from one agent to other, but two agents that want to establish a commercial relationship share at least one common variable in their utility functions.

We wish to find an allocation in the original graph representing the optimal supply chain. An allocation is a sub-graph  $(X', E') \subseteq (X, E)$ . For  $X_i, X_j \in V'$ , an edge between  $X_i$  and  $X_j$  means that agent  $X_j$  provides goods to agent  $X_i$ . Among all the feasible supply chains, we search for the optimal supply chain, as being the one that gives to the end consumer the highest utility according to her utility function, within the constraints of the underlying suppliers.

In order to solve the problem stated above, we consider the utility functions as factors and we propose the transformation of the original graph into a graphical model - a cluster graph. For this transformation we will remove the arrows from the original graph and we will consider clusters over the variables of the utility function of each agent. Here, we use the theoretical foundation about graphical models presented in chapter 4.

In order to maintain the decentralized supply chain formation mechanism and to preserve the original graph topology, we create a cluster for each agent and we assign the factors corresponding to her utility function to her related cluster.

The resulted graph will be an cluster graph where the nodes are clusters  $C_i \subseteq \{I_1, I_2, \dots, I_n\}$  and an edge between a cluster  $C_i$  and a cluster  $C_j$  is associated with a subset  $S_{i,j} \subseteq C_i \cap C_j$ . The subset  $S_{i,j}$  contains all the common issues that the agents are talking about, the ones that they are interested in getting to an agreement, in order to form the supply chain.

The number of variables in the utility functions might be different for two adjacent clusters and may include subjective variables that the participants don't need to agree on. In order to eliminate the variables that clusters don't talk about, we run a multiple step process. At each step:

- (a) The variables that the two adjacent clusters don't talk about are eliminated trough factor maximization, in order to generate a new factor  $\lambda_i$  with a smaller scope.  $\lambda_i$  is used for computing other factors.
- (b) A new factor  $\tau_i$  is created trough factor summation between the initial adjacent cluster and the new generated smaller factor  $\lambda_i$ .

Considering the process above in terms of message passing, the factors  $\tau_i$  represent clusters and  $\lambda_i$  messages that are generated from cluster  $\tau_i$  and sent to another cluster



$\tau_j$ . These smaller factors  $\lambda_i$  that are produced by  $\tau_i$  and consumed by  $\tau_j$  give the messages that are passed between the two agents.

Connecting all the components described above, in the following we describe the Multiple Contract Parameters Belief Propagation (MCP-BP) algorithm for supply chain formation:

- (a) Create a cluster  $C_i$  for every possible participant in the supply chain  $X_i$
- (b) Construct initial potentials  $\Theta_k = U_k(v)$ , considering utility functions as factors
- (c) Assign each factor  $\Theta_k$  to a cluster  $C_k$  such that  $Scope[\Theta_k] \subseteq C_k$
- (d) For each possible allocation sub-graph do (starting from underlying suppliers to the final consumer and back)
  - i. Pass message from a cluster  $C_x$  to a cluster  $C_y$  according to

$$\lambda(J)_{C_x \rightarrow C_y} = \max_{I \setminus J} \Theta_x(\bar{I}) \quad (5.1)$$

where  $I$  is the set of variables that are linked to factor  $\Theta_x$ ,  $\bar{I}$  are the joint states for all variables in  $I$ ,  $J$  is the set of variables that clusters  $C_x$  and  $C_y$  share

- ii. Assess beliefs at cluster  $C_y$  according to

$$\tau = \Theta_y(\bar{I}') + \sum_{k \in N_y} \lambda_{C_k \rightarrow C_y}(J) \quad (5.2)$$

where  $I'$  is the set of variables that are linked to factor  $\Theta_y$ ,  $\bar{I}'$  are the joint states for all variables in  $I'$ ,  $N_y$  are the neighborhood clusters of  $C_y$

- (e) Evaluate the utilities obtained by the final consumer and find the optimal supply chain allocation as the one that maximizes the utility of the final consumer

In the following chapter, we will focus on the supply chain formation and risk management emphasizing two business case studies. In order to deal with risk in SCF, we will use of the principle of maximum expected utility - described in section 6, which is the foundation for decision making under uncertainty.

## 2. MCP-BP performance

In what follows, we provide bounds for memory and communication requirements for storing agent preferences and exchanged messages in the proposed MCP-BP algorithm.

**Memory requirements:**

Each agent needs to store preferences over variables' states that are part of her utility function. Let  $i$  be the maximum number of variables in the utility function and  $k$  the maximum number of states for each parameter. Hence, the memory that an agent needs to store his preferences is  $\theta(k^i)$ . Note that the memory requirements depend only upon the number of parameters and the number of states for each parameter. Following the literature regarding supply chain contracts presented in Chapter 2, the maximum number of parameters for a contract is about eight. The preferences of each agent over the states of the variables are modelled using utility function, and their preferences are the same no matter how many agents will participate in the supply chain. Hence we can say that our approach is scalable.

**Communication requirements:**

Two agents that are interested in establishing a commercial relationship exchange a message regarding the variables they share in their utility functions. Let  $j$  be the maximum number of shared variables between two agents, the message size will be  $\theta(k^j)$ . Let  $p$  be the number of possible allocation sub-graphs and let  $n$  be the maximum number of agents in each possible allocation sub-graph. The number of messages that are sent from the underlying suppliers to the end consumer are  $(n - 1)$ . The number of messages that are sent back from the consumer to the suppliers are also  $(n - 1)$ . Hence, the communication requirements for supply chain formation mechanism is  $\theta(p * 2 * (n - 1) * k^j)$

We empirically evaluate the memory and communication requirements for the topology networks (Simple, Two consumers, Greedy Bad, Unbalanced, Many Consumers) used above for the evaluation of the supply chain formation solutions. For our experiments we used two types of data sets:

- (a) data sets that we called "few parameters" that have 2-3 parameters in the utility functions with 1-2 shared parameters between them.

(b) data sets that we called "many parameters" that have 7-8 parameters in the utility functions with 5-6 shared parameters between them.

For each of the data sets with "few parameters" and "many parameters", we have set the parameters that every participant is interested in to include in the contracts in the supply chain. Afterward, for each type of network, we generated data sets with random values for utility functions of each participant in the network. Then, we created files following the LibDAI structure (which has been described in section ??), and we have uploaded them to the DataBricks cloud for running our experiments.

Figures 5.1 and 5.2 depict the memory requirements for storing preferences for the two types of data sets. They show that the memory needed to store preference increases with the number of parameters in the utility functions. In real world scenarios, in most cases, the number of parameters does not exceed eight parameters, so we can conclude that is the bound memory requirement for the types of supply chain analyzed when all the parameters have two states.

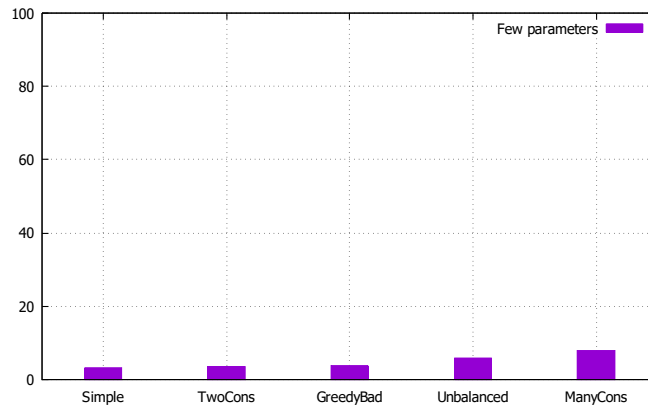


Figure 5.1: Memory requirements(KB) for storing preferences - few parameters

Figure 5.3 and 5.4 show that communications requirements increase according to the number of shared parameters. In figure 5.4 the number of shared parameters is 5-6 instead of 1-2, as in figure 5.3, so the communication requirements are bigger. But, in real world scenarios as the most contracts have about eight parameters maximum, means that the maximum average parameters would be approximate six, so we can say that the memory requirements for the types of supply chain depicted in figure 5.4 would be the bound when the number of contract parameters of the entities involved

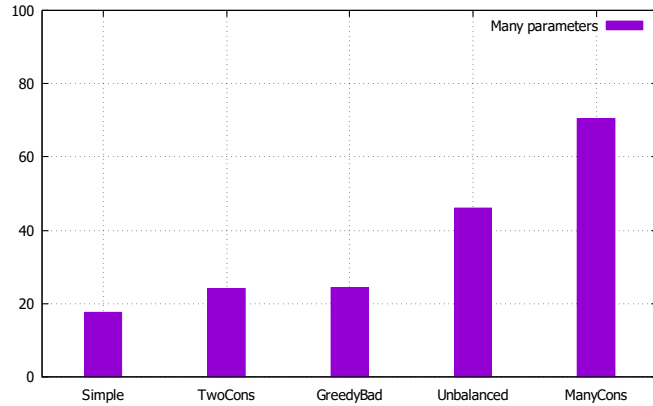


Figure 5.2: Memory requirements(KB) for storing preferences - many parameters

in the supply chain are 7-8. Note that the names in the  $x$  axis in figures 5.1 to 5.4 correspond to the network structures described in (Walsh & Wellman 2003).

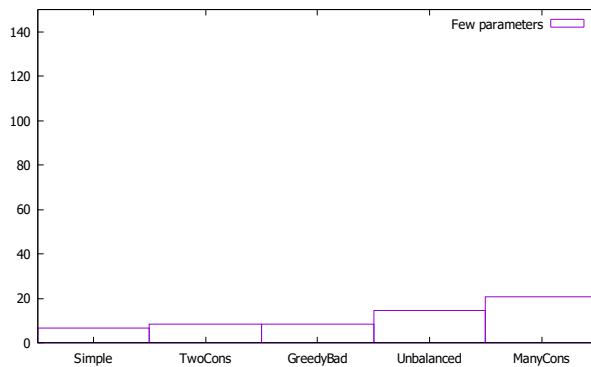


Figure 5.3: Communication requirements(KB) - few parameters

**3. MCP-BP against other SCF algorithms** Our proposed approach is able to provide in a decentralized setting the following benefits over the state of the art approaches:

- (a) It is able to deal with multiple contract parameters making it a strong candidate for applying it in real world scenarios.
- (b) It extends the myopic approach for assessment of the optimal supply chain. The previous approaches evaluated the optimal supply chain based on the difference between consumption values and production costs while our approaches evaluates the optimal supply chain based on utility functions. In real world scenarios the

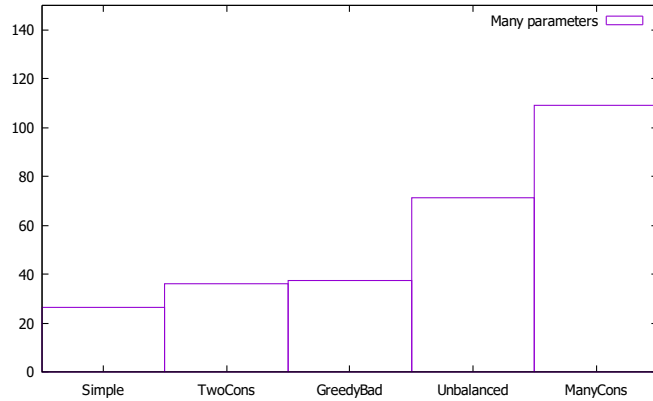


Figure 5.4: Communication requirements(KB) - many parameters

preference over a supply chain or another depends on multiple issues that involve contract parameters that participants in the supply chain need to agree on, but also subjective parameters specific to each participant.

- (c) It overcomes the limitation of previous approaches in scenarios involving complementary products. In network structures where complementary products setting existed, the solutions provided by previous approaches were able to satisfy only one consumer at a time. Our encoding and message passing mechanism over cluster graph overcomes this limitation and is able to provide solutions where multiple consumers are satisfied.
- (d) The encoding used in our approach addresses the sub-optimal solutions issues that appear in previous approaches in settings where resource scarcity appears. Hence, as long as the quantities required by the upper levels producers do not exceed the production capabilities, MCP-BP is able to provide optimal solutions to networks with resource scarcity issues.
- (e) It provides the possibility to incorporate risk in the assessment of the optimal supply chain by using the measure of maximum expected utility. In chapter 6 we will show in two business applications how risk can be incorporated in the decision making mechanism.
- (f) By using utility functions in order to encode the options of the participants, we are able to incorporate multiple contract parameters meanwhile the preferences are not dependent upon the number of participants in the network. The memory

requirements is dependent upon the number of contract parameters and the number of states of these parameters, hence, our approach is scalable even in markets characterized by a high degree of competition

- (g) The message size is dependent upon the number of shared parameters for the contract between two participants. The message size might be bigger than in other approaches like RB-LBP, because it incorporates multiple parameters, but the number of exchanged messages between two participants is lower, as a result of our encoding of the SCF problem in a cluster graph.

We must note that our approach brings several benefits over the state of the art approaches but it may have a decreased performance when contract parameters take values on continuous domains. The memory needed to store the preferences of the participants and the communication requirements will grow with the size of the domain of the parameters involved in the utility functions of the participants in the supply chain.

## Chapter 6

# Business Application Cases

In this chapter we present two case studies, to illustrate how the SCF framework introduced in chapter 5 can be used in practice. The two cases depict scenarios from different industries, with different life time for the supply chain. For the ISD project the supply chain has a limited life time, meanwhile the petroleum industry case study, considers the supply chain in a "business as usual" context. Moreover the position in the supply chain of the entities that the two case studies focus on is different. In the first case study, the agent is at the top of the supply chain, meanwhile in the second case study, the agent is in the middle of the supply chain, as in the case study we focus on a refinery.

### 1. ISD Complex Projects

The increasing projects' complexity provide new challenges regarding management and development. In complex projects scenarios where the outcome is composed of several deployed components, guaranteeing specific contract requirements for the prime contractor of the project is a real challenge.

The current case study proposes to address this complexity and the emerging issues arising from it. We consider the scenario of a complex IS development project, the IS being a collection as a whole of high level different technological components like software components, data base management systems components, communication components, security components and the connections between them. These components are provided by subcontractors as the IS as a whole cannot be provided by a prime contractor. The subcontractors act in a globalization context and span over geographical borders.

An emergent issue in the scenario stated above is composite decision making. In order to address the composite decision making situation that arise in complex project scenarios, we propose using utility functions as a means for incorporating in agreed contracts besides cost, parameters like: quality, delivery constraints etc.

A second issue that arises from the increased complexity of ISs is the increased risks. For example the prime contractor might have a fine stipulated in his contract with the primary client for every day of delay in delivering. It is often difficult to decide for the prime contractor to which sub-contractor to assign a critical activity. It is challenging to anticipate if assigning it to a reliable sub-contractor, that is higher-priced, has benefits over assigning it to the lower-priced sub-contractor that also promises to accomplish the task, although we might suspect that he might not be able to do it. Thus instead of using traditional risk analysis and modelling techniques like Expected Monetary Value (EMV) we use Expected Utility in order to incorporate risk in decision making.

Figure 6.1 describes the influence on the expected utility  $\mu$  of variable risk and an action (the choice he makes over the possible partners) taken by a subcontractor based on his utility function.

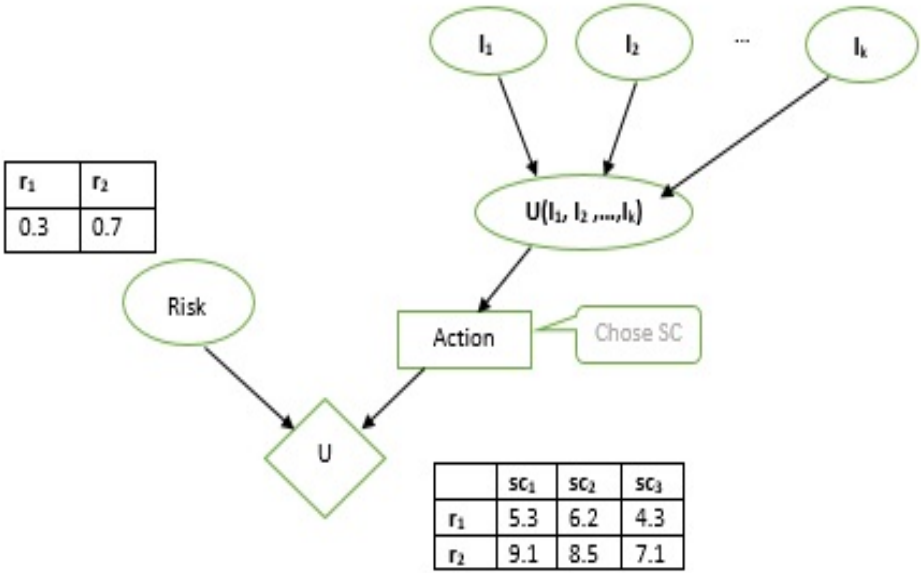


Figure 6.1: Influence diagram for an ISD project (Covaci et al. 2017)



Each agent shares states variables with possible partners in the supply chain  $(I_1, I_2, \dots, I_k)$ . The action variable which is different from the states variables provides means for agents to choose among partners which maximize their utility. The utility values are calculated according to each own utility function. In the proposed decision making mechanism the risk variable takes the form of a probability distribution (denoted  $P(y|a)$  in equation ??), that incorporates agent previous experience in achieving similar tasks, the agent reputation etc.

## 2. Petroleum Industry

The current case study considers the problem of supply chain formation and risk management in the petroleum industry. This industry has a strategic position as it is the base for other economic activities of any country. The petroleum industry is faced with volatile feed stock costs, cyclical product prices and seasonal final products demand. We consider the position of a refinery as it is at the middle of the integrated petroleum supply chain, between the upstream and downstream. It procures crude oil from upstream assessing the price, quality, time of delivery and distance to the refinery for deciding the optimal acquisition. Additionally, the refiner is monitoring the price evolution and managing the inventory. The manufacturing activities of the refiner requires thoroughly planning and scheduling the production levels and supply chains for all the derivatives and feed stocks for petrochemical industry using tools for decision making in order to estimate market opportunities and threats under volatile market conditions.

We are modelling decision support for a refinery using the influence diagram in Figure 6.2 considering uncertainties in crude oil prices and demand in petrochemical products.

The price for crude oil and predicted demand are in the form of a probability distribution and we will notate it with  $P(d)$ . The price variable tells the probability that the price of the crude oil will go up, go down or stay at the same level  $(p_0, p_1, p_2)$ . The demand variables tells the probability for the evolution of the demand  $(d_0, d_1, d_2)$  for petrochemical products when the price for the raw material will change  $P(d|p)$ . We introduce, an action variable that provides a decision rule  $\delta A$  at action node A (Action), that is conditional probabilistic distribution  $P(A|Parents(A))$ . Parents (A)

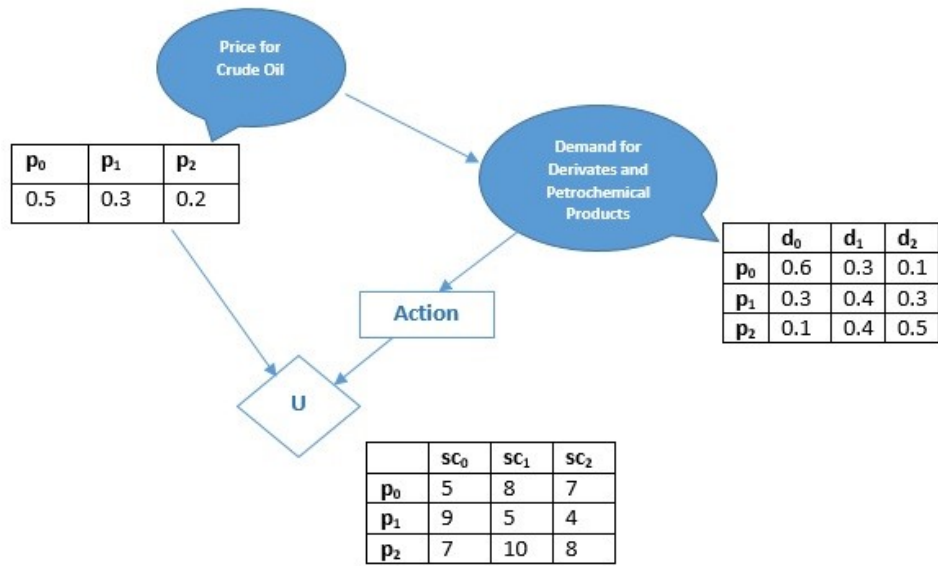


Figure 6.2: Influence Diagram for a refinery

are the variables that the agent observed prior to making a decision, in the example below being the predicted demand evolution ( $P(A|d)$ ). Hence, the action variable provides the agent with a decision situation  $D$  and the agent will choose from the set of possible actions the one that is maximizing the expected utility.

The case studies presented in two completely different scenarios emphasize the flexibility of the proposed mechanism, hence our approach can be applied in any network of production or services which decompose tasks or use exchange relationships that spans multiple levels.

## Chapter 7

# Conclusions and future work

As we have emphasized in Chapter 3, the Supply Chain Formation (SCF) problem has been deeply discussed in the literature regarding multi-agent systems, several approaches being proposed. Based on a literature review, we were able to create a theoretical framework for automated supply chain formation with respect to three dimensions:

- The approach used regarding the existence of a central authority
- The techniques employed for information exchange between entities in the supply chain
- Usage of multi-unit dimension or bundles for the traded goods.

We furthermore identified the following important gaps and issues in the existing research literature regarding supply chain formation:

- Parameters used in order to pairwise suppliers/consumers are limited usually only at the price and sometimes the number of units for traded goods.
- Automating supply chain formation poses an intricate coordination problem to firms that must simultaneously negotiate production relationships at multiple levels of the supply chain, but in the existing literature the resulted supply chains are assessed only using a profit optimization function for the end-consumer.
- The possible risks associated with participating entities in the supply chain are not considered.

At the base of Industry 4.0 stands the digital supply chain, being a key component for the operations of a manufacturing or distributing company. The digitization of supply chains requires intelligent and efficient algorithms that can capture the complexity of real scenarios and can create innovative end-to-end mechanisms that connect suppliers and customers. The current thesis proposed a decentralized mechanism for Supply Chain Formation problem. As opposed to the previous decentralized approaches, our approach translates the SCF optimization problem not as a profit maximization problem but as a utility maximization. Hence, it incorporates multiple parameters and uses utility functions in order to find the optimal supply chain. The current approach is closer to real life scenarios than the previous approaches that were using only cost as a mean for pairwise agents because it uses utility functions for entities in the supply chain to make decision. Moreover our approach overcomes the limitations of previous approaches by providing means for dealing with complementary products. It also offers means to incorporate risk in decision making situations under uncertainty.

The limitation of our approach reveals in situations where the parameters can take values over continuous domains. In these cases, storing the preferences for every agent needs a considerable amount of memory, hence the proposed approach would encounter efficiency issues. As a future work we intend to improve performance of the proposed mechanism when we are dealing with parameters that take values over a continuous domain.

# Bibliography

Arshinder, Kanda, A. & Deshmukh, S. (2008), ‘Supply chain coordination: Perspectives, empirical studies and research directions’, *International Journal of Production Economics* **115**(2), 316 – 335.

**URL:** <http://www.sciencedirect.com/science/article/pii/S0925527308001904>

Behzad, H. & Wiesaw, K. (2010), ‘Coordinating contracts in scm: A review of methods and literature’, *Decision Making in Manufacturing and Services* **4**, 5–28.

Bishop, C. M. (2006), *Pattern recognition and machine learning*, Springer, New York.

Covaci, F. L. (2017), Industry 4.0 - towards automated supply chain formation, in M. Schoop & M. D. Kilgour, eds, ‘Doctoral Consortium of the 17Th International Conference on Group Decision and Negotiation’, Vol. 17-2017 of *Hohenheim Discussion Papers In Business, Economics and Social Sciences*, pp. 27–36.

Covaci, F. L., Bologa, C. S. & Silaghi, G. C. (2017), Expected utility and risk management in complex projects, in N. Paspallis, M. Raspopoulos, C. Barry, M. Lang, H. Linger & C. Schneider, eds, ‘Proceedings of the 26th International Conference on Information Systems Development (ISD2017)’, Association for Information Systems, pp. 1–9.

Fishburn, P. C. (1968), ‘Utility theory’, *Management Science* **15**(5), 335–378.

Hohn, M. (2010), *Relational Supply Contracts - Optimal Concessions in Return Policies for Continuous Quality Improvements*, Springer.

Koller, D. & Friedman, N. (2009), *Probabilistic graphical models: principles and techniques*, MIT Press.

Kreps, D. A. (1990), *A course in microeconomic theory*, Princeton University Press.

- Shafer, G. & Shenoy, P. (1990), ‘Probability propagation’, *Annals of Mathematics and Artificial Intelligence* **2**(1-4), 327351.
- Tsay, A. (1999), ‘The quantity flexibility contract and supplier-customer incentives’, *Management Science* **45**, 1339–1358.
- Wainwright, M. J. & Jordan, M. I. (2008), *Graphical Models, Exponential Families, and Variational Inference*, Now Publishers Inc.
- Walsh, W. E. & Wellman, M. P. (2003), ‘Decentralized supply chain formation: A market protocol and competitive equilibrium analysis’, *Journal of Artificial Intelligence Research* **19**, 513–567.